For Online Publication

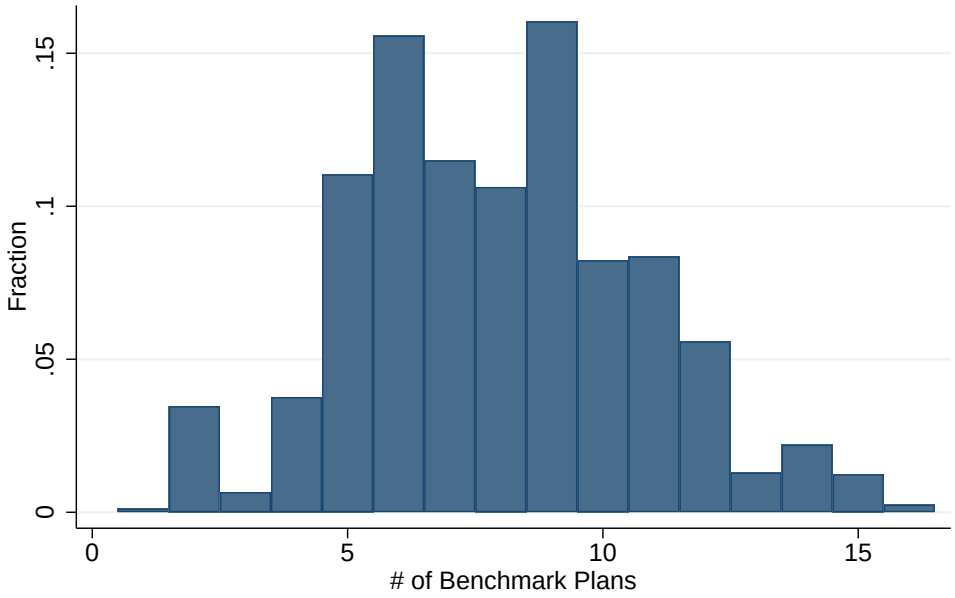
Appendix for:

Rationing Medicine Through Bureaucracy: Authorization Restrictions in Medicare

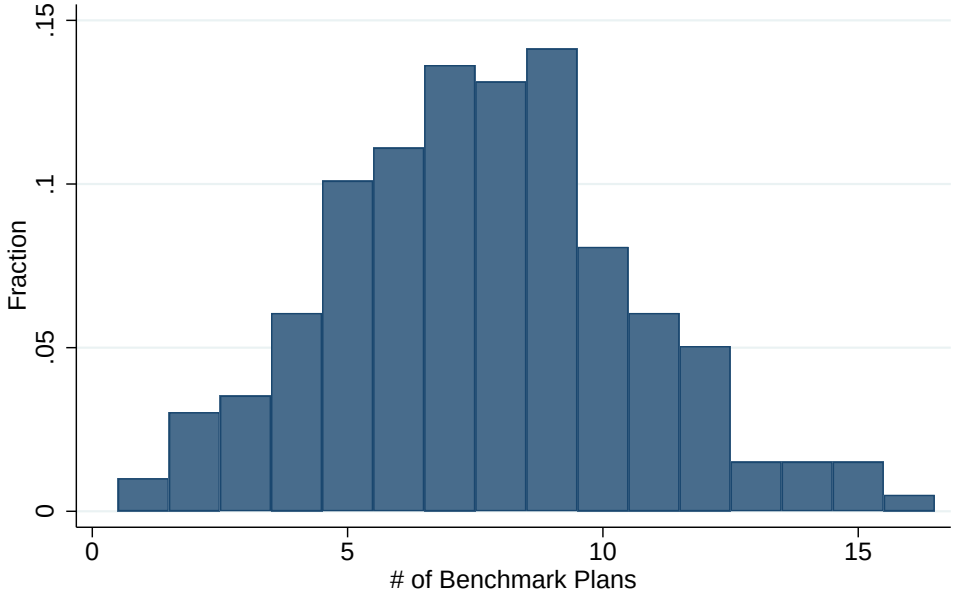
A Additional Figures

Appendix Figure A1: Distribution of Number of Benchmark Plans in Region-Year

(a) Weighted by Number of Beneficiaries

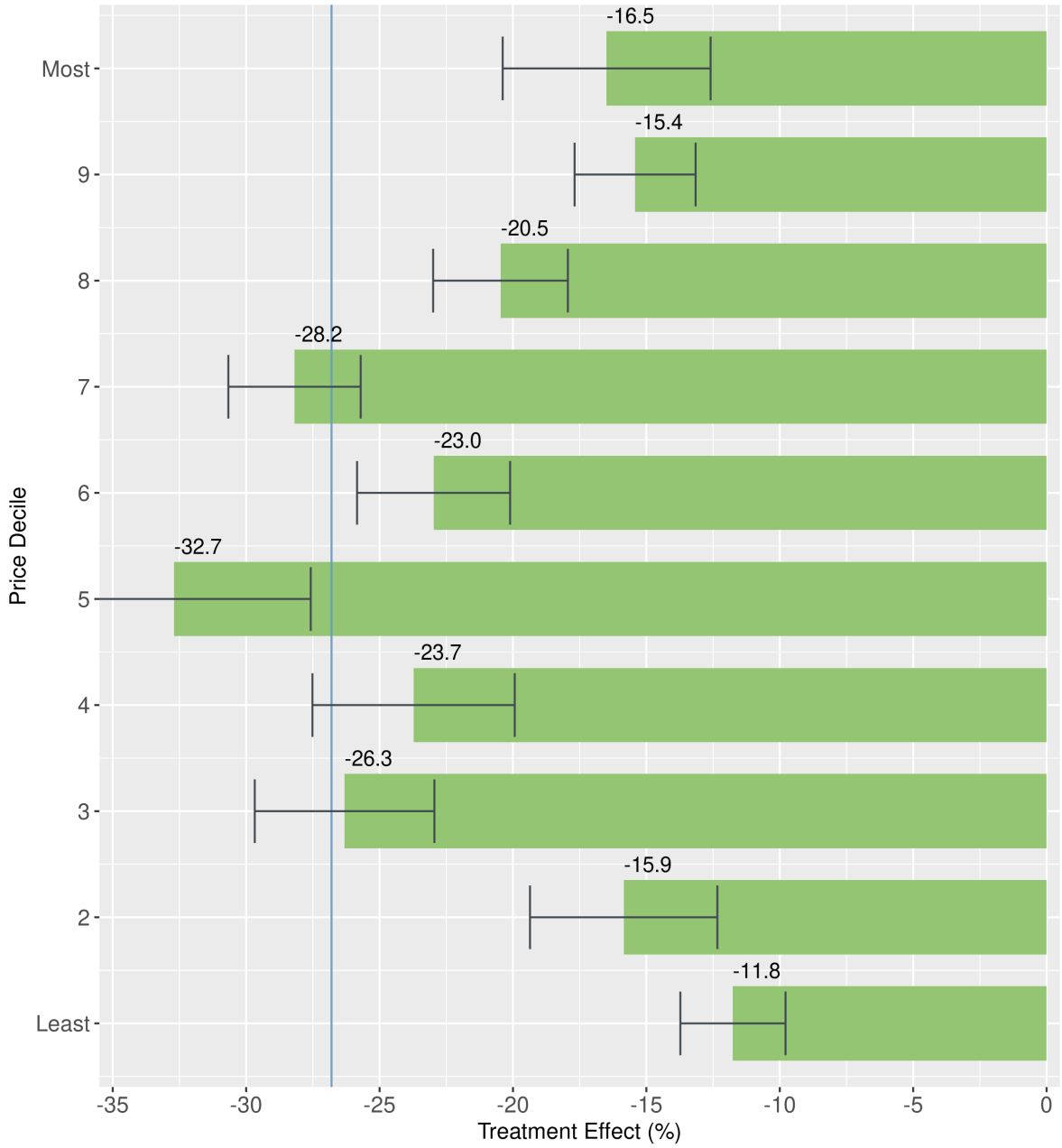


(b) Unweighted



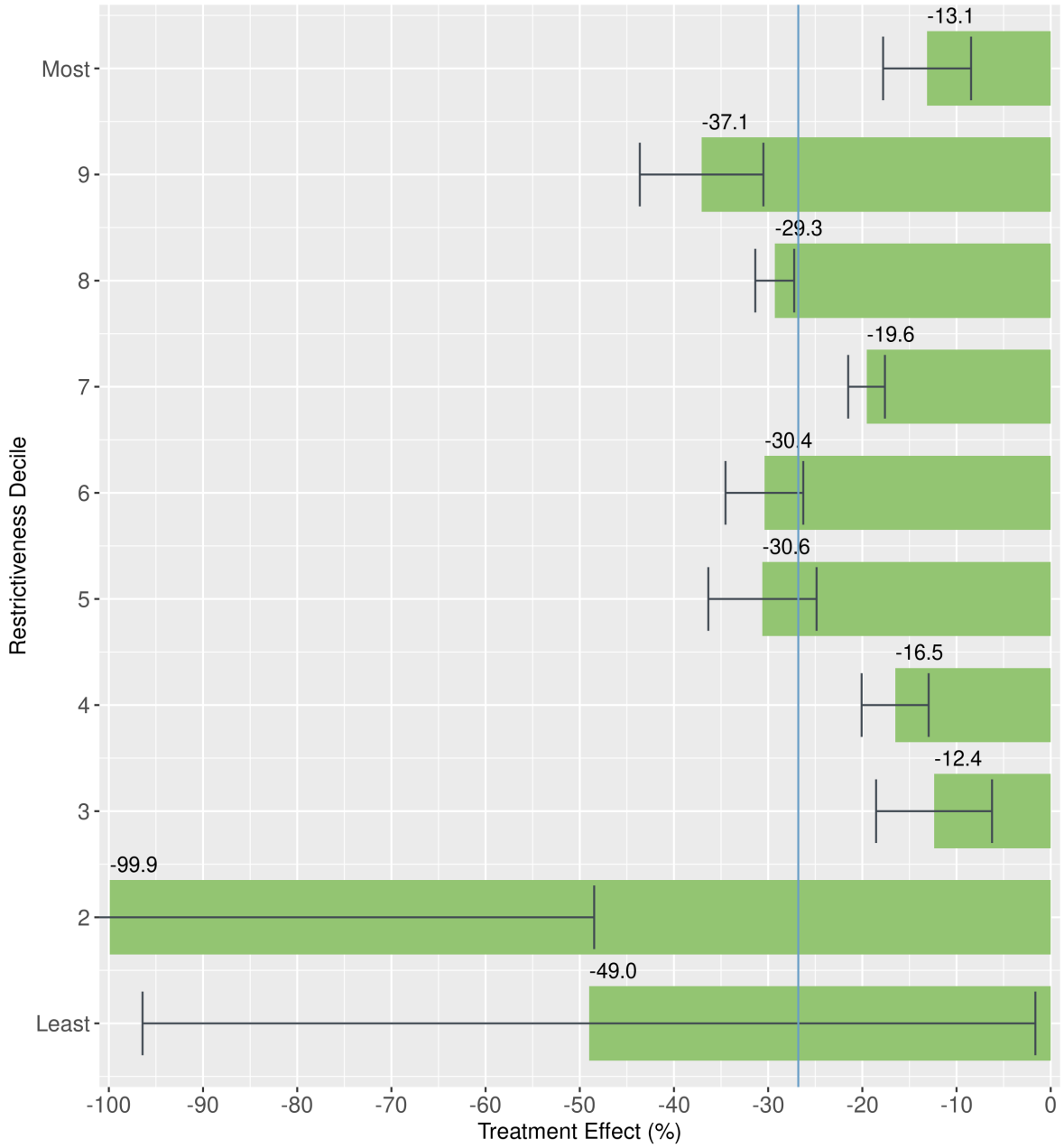
Notes: This set of figures plots the distribution in the number of benchmark plans across the pairs of Part D service region-years. The top figure presents this distribution weighting all Part D service region-year pairs equally, while the bottom weights Part D service region-year pairs by the number of beneficiaries in our sample enrolled under each.

Appendix Figure A2: Heterogeneous Effects of Prior Authorization on Utilization by Drug-Year Price Deciles



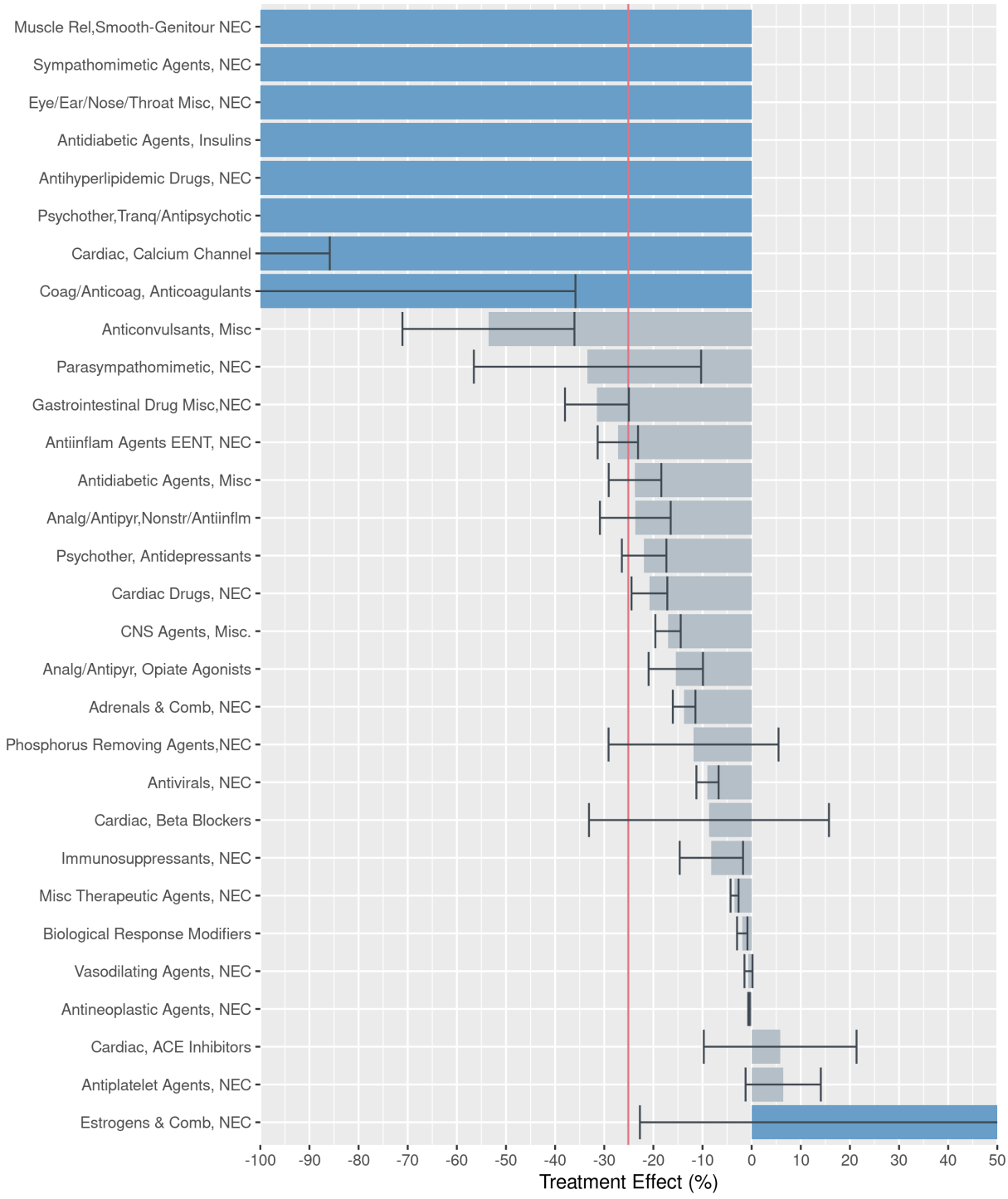
Notes: This figure presents the results from regressions of beneficiary utilization of a given drug on an indicator for whether the beneficiary's assigned plan put a prior authorization restriction on that drug. We run separate regressions on groups of drug-year pairs, where pairs are grouped into decile based on their price per day supply. Effects are presented in the percent change due to prior authorization relative to a control mean, reweighted as described in 3.3.

Appendix Figure A3: Heterogeneous Effects of Prior Authorization on Utilization by Drug-Year Restriction Rate Deciles



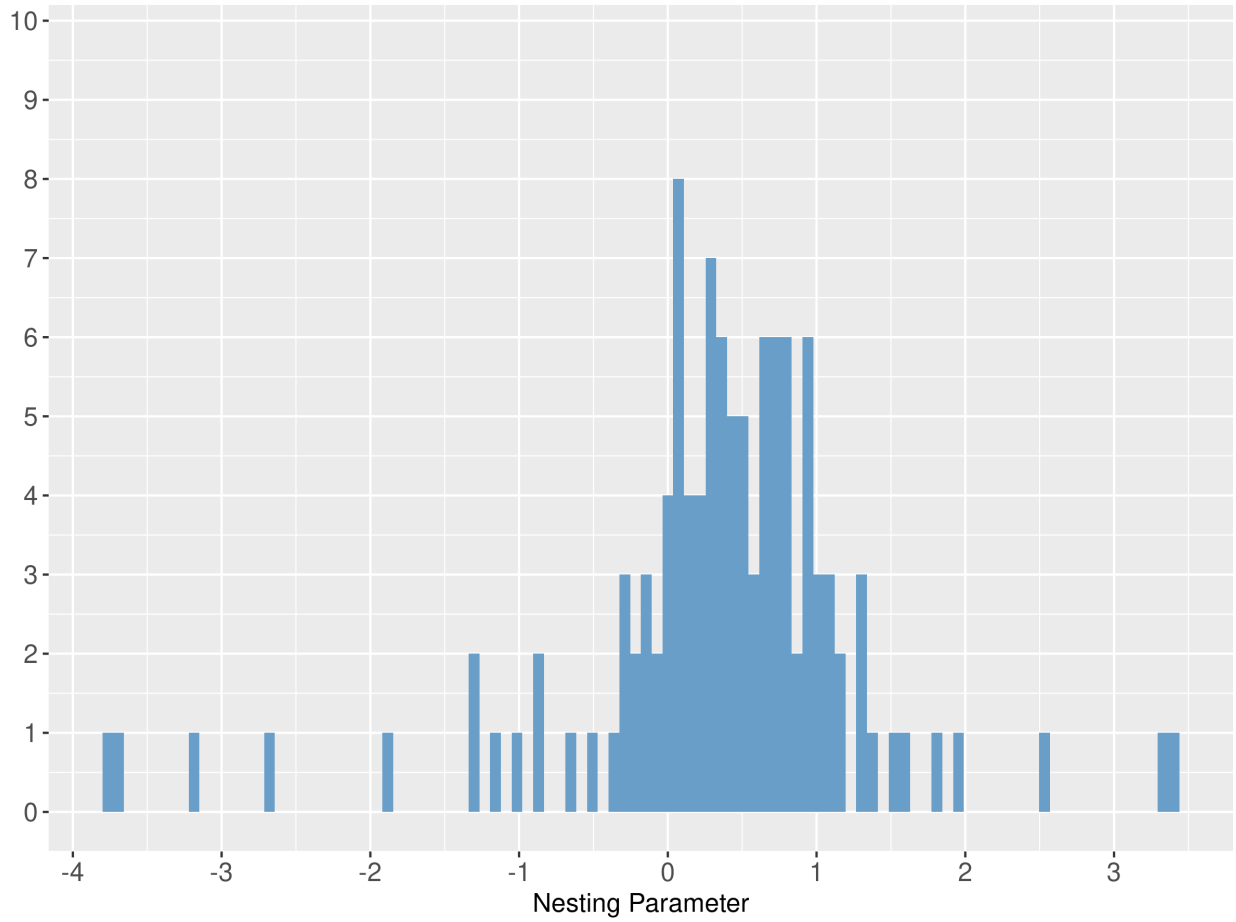
Notes: This figure presents the results from regressions of beneficiary utilization of a given drug on an indicator for whether the beneficiary's assigned plan put a prior authorization restriction on that drug. We run separate regressions on groups of drug-year pairs, where pairs are grouped into decile based on the share of plans in that year that put the drug under a prior authorization restriction. Effects are presented in the percent change due to prior authorization relative to a control mean, reweighted as described in 3.3.

Appendix Figure A4: Heterogeneous Effects of Prior Authorization on Utilization by Class

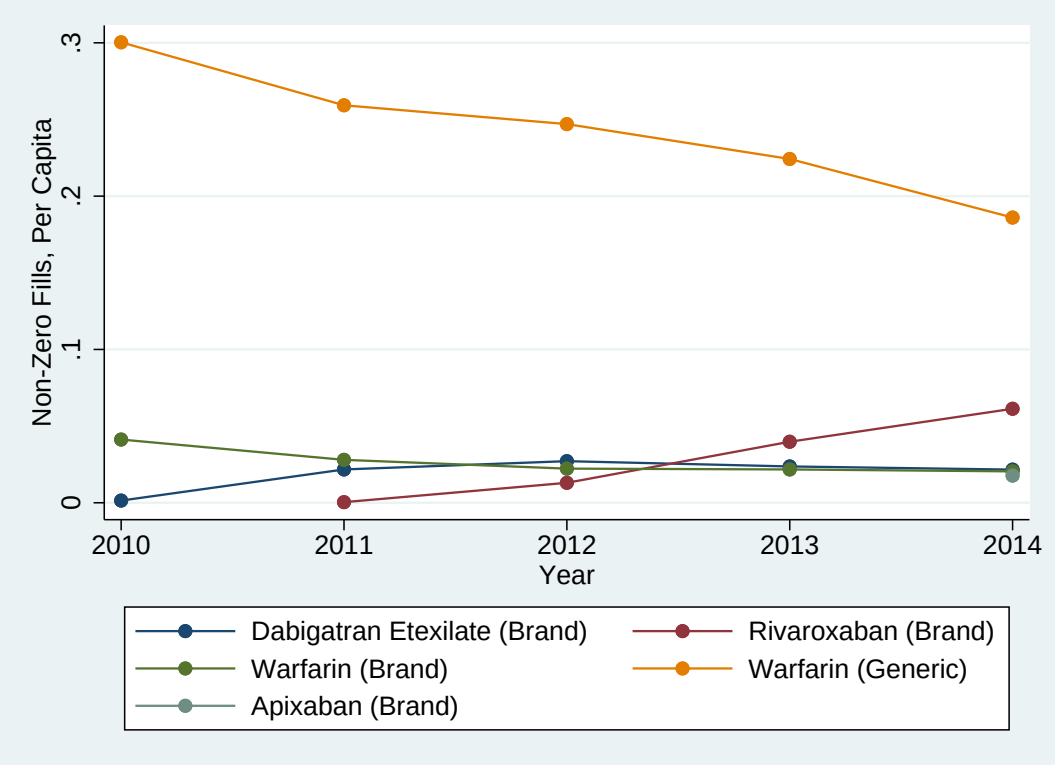


Notes: This figure presents the results from regressions of beneficiary utilization of a given drug on an indicator for whether the beneficiary's assigned plan put a prior authorization restriction on that drug. We run separate regressions on each drug therapeutic class. We report results only for the top 30 classes by total spending. Effects are presented in the percent change due to prior authorization relative to a control mean, reweighted as described in 3.3.

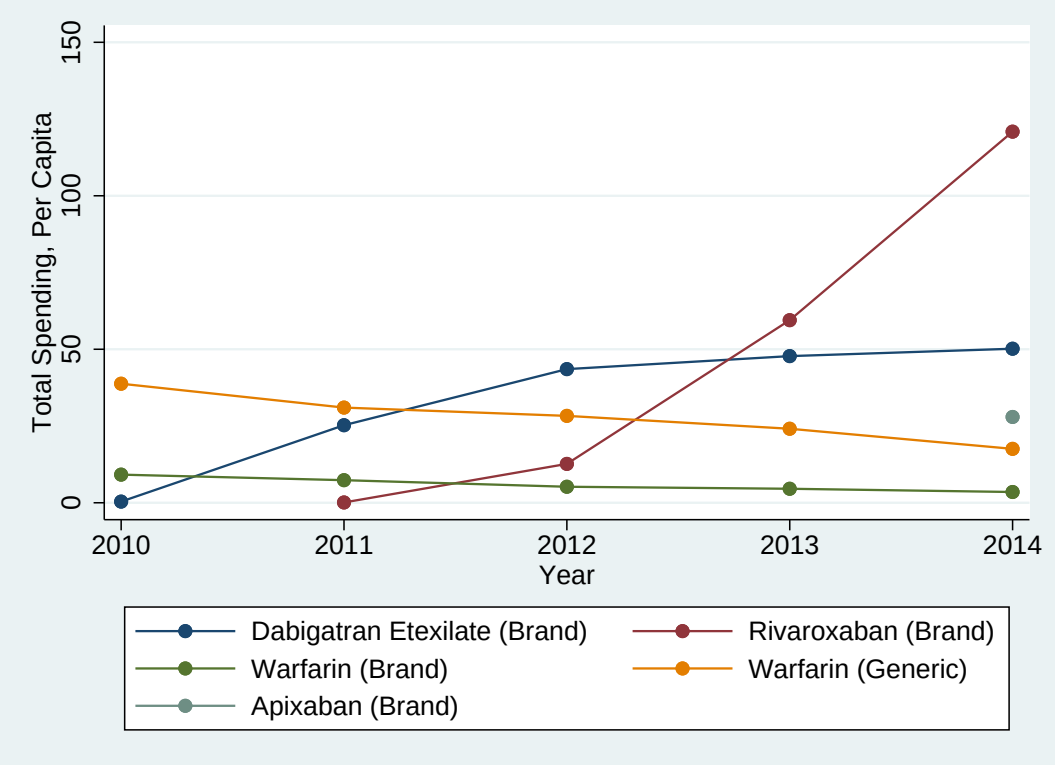
Appendix Figure A5: Distribution of Nesting Parameter Across Classes



Notes: This figure presents a histogram of estimates of λ, the nesting parameter in our nested logit demand system. Each underlying observation in this figure is an estimate for a specific therapeutic class.



Appendix Figure A6: This figure presents the share of patients filling each of these oral anticoagulants at least once during the year, across time.



Appendix Figure A7: This figure presents the per-patient yearly spending on each of these oral anticoagulants, across time.

B Additional Tables

Appendix Table A1: Prior Authorization Frequency for Top Drug Classes by Medicare Part D Spending

	Spending per beneficiary year (USD)	% spending with prior auth	% fills with prior auth
Biological Response Modifiers	94	69.6	68.1
Immunosuppressants	65	66.3	54.7
Antineoplastic Agents	99	57.7	13.9
Adrenals & Comb	86	3.0	11.6
CNS Agents, Misc	94	17.6	6.9
Cardiac Drugs	88	12.4	5.9
Antidiabetic Agents, Misc	110	15.0	5.7
Estrogens & Comb	25	1.2	5.4
Bone Resorption Inhibitors	22	9.0	4.8
Misc Therapeutic Agents	58	15.0	4.0
Tranq/Antipsychotic	185	6.9	3.6
Sympathomimetic Agents	27	2.1	3.4
Antidepressants	93	7.7	3.3
Gastrointestinal Drug, Misc	132	2.8	3.2
Anticoagulants	47	14.5	2.8
Muscle Relaxants	36	1.9	2.3
Antivirals	120	14.6	2.1
NSAIDs	37	10.0	1.6
Anticonvulsants, Misc	60	4.4	1.6
Vasodilating Agents	27	44.6	1.5
Parasympathomimetic	42	3.2	1.5
Antiplatelet Agents	70	0.6	1.4
Antihyperlipidemic Drugs	212	2.7	1.1
Cardiac, Calcium Channel	49	1.5	1.0
Antidiabetic Agents, Insulins	158	0.6	0.9
Opiate Agonists	92	3.5	0.7
Eye/Ear/Nose/Throat Misc	44	1.2	0.6
Cardiac, Beta Blockers	45	0.5	0.5
Antiinflam Agents EENT	29	0.1	0.2
Anticholinergic	47	0.1	0.2

Notes: This table reports, for a set of therapeutic classes, the total spending per beneficiary-year, the share of spending where the drug being filled required a prior authorization restriction, and the share of prescription drug fills where the drug being filled required a prior authorization restriction. All statistics are limited to beneficiaries in our sample.

Appendix Table A2: First Stage Regressions with Further Specifications

			$\text{Auth}^{\text{Enrolled}}$			
$\text{Auth}^{\text{Assigned}}$	0.950	0.913	0.908	0.908	0.908	0.908
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
$\text{Excluded}^{\text{Assigned}}$	0.002	-0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			$\text{Excluded}^{\text{Enrolled}}$			
$\text{Auth}^{\text{Assigned}}$	0.003	0.002	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\text{Excluded}^{\text{Assigned}}$	0.950	0.918	0.905	0.905	0.905	0.905
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Drug FEs		X				
Drug-year FEs			X			
Drug-market-year FEs				X	X	X
Plan-market-year FEs					X	X
Substitution Controls						X
Number of drug-beneficiary-years			1,723,975,571			
Number of beneficiary-years			1,113,594			
Number of market-years			210			
Average plans per market-year			6.6			
Number of drug-years			12,554			

Notes: This table presents coefficient estimates from the 'first stage' regressions of indicators for whether the plan a beneficiary enrolled in during a given year placed prior authorization restrictions on or excluded a drug in that year, on indicators for whether the plan the beneficiary was assigned to placed prior authorization restrictions on or excluded that drug. In the upper panel, the outcome is whether the plan of enrollment restricted the drug in that year. In the lower panel, the outcome is exclusion rather than restriction. Each underlying observation is a beneficiary-drug-year tuple. Standard errors are clustered at the assigned plan and year level. Columns represent regressions with different sets of controls.

Appendix Table A3: Placebo Test: Formulary Status in Prior Year

	$\text{Auth}_{t-1}^{\text{Enrolled}}$	$\text{Excluded}_{t-1}^{\text{Enrolled}}$
$\text{Auth}_t^{\text{Assigned}}$	-0.001	-0.001
	(0.002)	(0.001)
$\text{Excluded}_t^{\text{Assigned}}$	-0.001	-0.003
	(0.001)	(0.001)
F-statistic	1	4
Number of drug-beneficiary-years	1,510,671,381	
Number of beneficiary-years	1,037,159	
Number of market-years	210	
Average plans per market-year	6.6	
Number of drug-years	11,906	

Notes: This table presents estimates from a set of 'placebo' versions of our first-stage regressions, where we regress indicators for whether the plan a beneficiary enrolled in during a given year placed prior authorization restrictions on or excluded a drug in the year before reassignment on indicators for whether the plan the beneficiary was assigned to placed prior authorization restrictions on or excluded that drug in a given year following reassignment. Each underlying observation is a beneficiary-drug-year tuple. Standard errors are clustered at the plan and year level. In columns (1), the outcome is whether the plan of enrollment restricted the drug in that year. In columns (2) the outcome is exclusion rather than restriction.

Appendix Table A4: Placebo Test: Utilization in Prior Year

	Spending	# Fills	# Days Supply	% Ever Filled
$\text{Auth}^{\text{Assigned}}$	-0.011	0.000	0.003	0.002
	(0.032)	(0.000)	(0.005)	(0.005)
Reweighted Control Mean	2.651	0.135	0.403	0.307

Notes: This table presents estimates from a set of 'placebo' utilization regressions, where we regress a beneficiary's utilization of a drug in the year before reassignment on an indicator for whether the drug was put under prior authorization restrictions in the plan that beneficiary was assigned to in a given year following reassignment. Each underlying observation is a beneficiary-drug-year tuple. Standard errors are clustered at the plan and year level.

Appendix Table A5: Placebo Test: Demographics

	Female	White	Age	Elixhauser Index$_{t-1}$
Auth$^{\text{Assigned}}$	-0.000	-0.000	0.002	0.001
	(0.000)	(0.000)	(0.001)	(0.000)
Excluded$^{\text{Assigned}}$	-0.000	0.000	-0.006	-0.002
	(0.000)	(0.000)	(0.001)	(0.000)
Control Mean	0.583	0.614	62.6	3.56
Number of drug-plan-years			2,149,673	

Notes: This table presents estimates from a set of 'placebo' utilization regressions, where we regress indicators for a a beneficiary being in certain demographic groups on an indicator for whether the drug was put under prior authorization restrictions in the plan that beneficiary was assigned to in a given year following reassignment. Each underlying observation is a beneficiary-drug-year tuple. Standard errors are clustered at the plan and year level.

Appendix Table A6: Estimates of the Effect of Prior Authorization Restrictions on Utilization: Additional Specifications

	(7)	(8)	(9)
$Auth^{Assigned}$	-0.107	-0.090	-0.108
	(0.004)	(0.003)	(0.005)
$Auth^{Sub}$	0.049	0.391	0.049
	(0.0043)	(0.0186)	(0.0065)
PA % Effect	-26.7	-22.4	-26.7
Control Mean		1.305	
Reweighted Control Mean	0.403		0.395
Drug-market-year FEs	X	X	X
Plan-market-year FEs			X
Substitution Controls	X	X	X
Plan-by-cost FEs	X		
Plan-by-class FEs		X	
Number of drug × beneficiary-years	1,723,975,571		1,237,515,645
Number of market years		210	
Average plans per market-year		6.6	
Average beneficiaries per plan		803	
Average drugs per year	1569.2		1460.2

Notes: This table presents coefficient estimates from regressions of a beneficiary's utilization of a drug in a given year on an indicator for whether the drug was put under prior authorization restrictions in the plan that beneficiary was assigned to in that year. Each underlying observation is a beneficiary-drug-year tuple. Regressions include plan-market-year and drug-market-year fixed effects. Prior authorization of substitute drugs is mean prior authorization status of all other drugs within the class, where drugs are weighted by their average expenditure across all plans in the sample. Standard errors are clustered at the assigned plan and year level. Columns represent regressions with different sets of controls, except for the final column, which represents a version of the main regression specification that drops all observations where the drug in question was excluded. This table presents specifications not otherwise presented in Table 5.

Appendix Table A7: Estimates of the Effect of Prior Authorization Restrictions on Alternative Utilization Outcomes

	Days Supply	Spending	Fills
$Auth^{Assigned}$	-0.156	-0.767	-0.005
	(0.057)	(0.155)	(0.000)
$Auth^{Sub}$	0.057	0.155	0.002
	(0.0065)	(0.0285)	(0.0002)
PA % Effect	-30.9	-21.2	-28.5
Control Mean	1.529	3.555	0.051
Reweighted Control Mean	0.504	3.613	0.017
R^2	0.969	0.831	0.966
Number of drug $\times$ beneficiary-years		1,732,564,415	
Number of market years		210	
Average plans per market-year		6.6	
Average beneficiaries per plan		807	

Notes: This table presents coefficient estimates from regressions of a beneficiary's utilization of a drug in a given year on an indicator for whether the drug was put under prior authorization restrictions in the plan that beneficiary was assigned to in that year. Each underlying observation is a beneficiary-drug-year tuple. Regressions include plan-market-year and drug-market-year fixed effects. Prior authorization of substitute drugs is mean prior authorization status of all other drugs within the class, where drugs are weighted by their average expenditure across all plans in the sample. Standard errors are clustered at the assigned plan and year level. Columns represent different outcomes. The three outcomes are, in order, total allowed net spending on the drug in the year, number of prescription fills for the drug in the year, and total days supply for the drug in the year.

Appendix Table A8: Estimates of Prior Authorization Per-Application Administrative Costs

Study	Setting	Method	Estimate
Bukstein et al. (2006)	Single allergist clinic,	Staff time at hourly wages,[a] mean	$17.77
Raper et al. (2010)	Single HIV clinic,	Staff time at hourly wages, plus materials costs, mean	$14.24
		Staff time at opportunity costs,[b] plus materials costs, mean	$27.35
CAQH (2013)	Many surveyed practices	Staff time at estimated global rates, mean	
		...for manual filing[c]	$18.53
		...for electronic filing	$5.20
Carlisle et al. (2020)	Single dermatology clinic	Staff time at hourly wages, median	$7.67

Notes: This table presents estimates from the literature on the per-application administrative costs associated with drugs restricted under prior authorization. All studies are in U.S. settings unless otherwise noted.

[a] In this method, the researchers convert employees' salaries to hourly wage equivalents, then price their time using those hourly equivalents.

[b] In this method, the researchers calculate the revenue the practice would have received if the nurse involved took the time spent on the prior authorization request and instead billed insurers for the time-equivalent number of 30-minute visits for established patients (CPT code 99213) at standard Medicare rates at the time. In their manuscript, Raper et al. (2010) incorrectly add their wage-equivalent and opportunity cost estimates together, which is incorrect since it double-counts the nurse's time.

[c] CAQH (2013) distinguish between the costs of filing manually (i.e., with a fax machine or phone) or electronically (through the internet). Few prior authorization requests during our period were electronic, so we only use the manual costs in our calibration exercise.

Appendix Table A9: Estimates of Prior Authorization Request Rejection Rates

Study	Setting	Services	Estimate
LaPensee (2003)	One Medicaid MCO	All drugs	4.4%
		Non-formulary drugs	3.7%
		Formulary drugs	7.1%
Delate et al. (2005)	Medicaid	Proton-pump inhibitors	4.9%
Raper et al. (2010)	Single HIV clinic	All drugs	33%
Initial application[a]			
U.S. OIG (2018)	All Medicare	All services	4.1%
	Advantage MCOs	and drugs	
Birdsall et al. (2020)	Academic health system	All drugs	
Initial application			15%
Final application			7.4%
Carlisle et al. (2020)[a]	Single dermatology clinic	Biologics	21.1%
Initial application		Other drugs	41.8%
Lee et al. (2020)[a]	Division of Vascular Surgery	Lower-extremity	6.1%
	New York University Hospital, 2017	venous procedures	
Wallace et al. (2020)	Single rheumatology clinic	Infusable drugs	
Initial application			21%
Final application			4%
Schwartz et al. (2021)	Large private insurer	Hosp. services	4.2%
		and drugs	
AthenaHealth[b]	Physician clients	All drugs	1.5%

Notes: This table presents estimates from the literature on the rejection rates associated with requests made for services and drugs restricted under prior authorization.

[a] This study does not report interpretable final application approval rates.

[b] https://www.athenahealth.com/prior-authorization. Last accessed on 07/13/22.

Appendix Table A10: Simulation of Moving From No Prior Authorization Restrictions to Status Quo (with Standard Errors)

	Total	Restricted Drugs	Unrestricted Drugs	No Drug
Change in	-3.57%	-21.8%	+0.72%	-
Spending	(0.84)	(4.25)	(0.05)	
Per Capita	-95.88	-111.57	+15.69	-
	(23.92)	(23.78)	(1.00)	
Change in	-0.65%	-28.9%	+0.58%	+0.06%
# Users	(0.13)	(3.17)	(0.02)	(0.01)
Per Capita	-0.065	-0.120	+0.056	+0.065
	(0.013)	(0.013)	(0.002)	(0.013)
Diversion	-	-100%	46.2%	53.8%
			(7.48)	(7.48)

Notes: This table replicates 6 but adds standard errors to the relevant estimates, given in parentheses under their respective estimate.

Appendix Table A11: Administrative Costs From Authorization Restrictions (with Standard Errors)

		Request Rejection Rate				
		0%	1.5%	4%	7.5%	15%
Paperwork Cost	$11.62	4.84	4.92	5.04	5.24	5.70
		(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
	$18.19	7.58	7.70	7.90	8.20	8.92
		(0.07)	(0.07)	(0.08)	(0.08)	(0.09)
	$21.72	9.05	9.19	9.43	9.79	10.65
		(0.09)	(0.09)	(0.09)	(0.09)	(0.10)
	$22.48	9.37	9.51	**9.76**	10.13	11.02
		(0.09)	(0.09)	**(0.09)**	(0.10)	(0.11)
	$31.30	13.04	13.24	13.59	14.10	15.35
		(0.13)	(0.13)	(0.13)	(0.14)	(0.15)
	$50	20.84	21.16	21.71	22.53	24.52
		(0.20)	(0.21)	(0.21)	(0.22)	(0.24)
	$100	41.68	42.31	43.41	45.06	49.03
		(0.40)	(0.41)	(0.42)	(0.44)	(0.48)
	$200	83.35	84.62	86.83	90.11	98.06
		(0.81)	(0.82)	(0.84)	(0.87)	(0.95)

Notes: This table replicates 7 but adds standard errors to the relevant estimates, given in parentheses under their respective estimate.

Appendix Table A12: Savings per Administrative Dollar From Authorization Restrictions (with Standard Errors)

		Request Rejection Rate				
		0%	1.5%	4%	7.5%	15%
Paperwork Cost	$11.62	19.80	19.50	19.01	18.31	16.83
		(4.83)	(4.76)	(4.64)	(4.47)	(4.11)
	$18.19	12.65	12.46	12.14	11.70	10.75
		(3.09)	(3.04)	(2.96)	(2.86)	(2.62)
	$21.72	10.59	10.43	10.17	9.80	9.00
		(2.58)	(2.55)	(2.48)	(2.39)	(2.20)
	$22.48	10.23	10.08	**9.82**	9.47	8.70
		(2.50)	(2.46)	**(2.40)**	(2.31)	(2.12)
	$31.30	7.35	7.24	7.06	6.80	6.25
		(1.79)	(1.77)	(1.72)	(1.66)	(1.52)
	$50	4.60	4.53	4.42	4.26	3.91
		(1.12)	(1.11)	(1.08)	(1.04)	(0.95)
	$100	2.30	2.27	2.21	2.13	1.96
		(0.56)	(0.55)	(0.54)	(0.52)	(0.48)
	$200	1.15	1.13	1.10	1.06	0.98
		(0.28)	(0.28)	(0.27)	(0.26)	(0.24)

Notes: This table reports estimated ratios of the spending reductions induced by the historical prior authorization restriction regimes implemented in Medicare Part D relative to the costs of paperwork. Each cell represents the estimate under a calibrated set of values for the application cost a and rejection rate r. Values above 1 indicate that prior authorization generates net financial savings, while values below it indicate net financial costs. Parenthetical terms denote bootstrap standard errors for their associated estimate.

Appendix Table A13: Spending and Utilization Effects from Applying Authorization Restrictions to Currently-Unrestricted Drugs

	Total	Unrestricted Drugs	PA/Ex Drugs	No Drug
Change in	-7.02%	-11.91%	+0.14%	-
Spending	-181.55	-249.79	+68.25	-
Per Capita				
Change in	-11.71%	-13.52%	+26.28%	+1.05%
# Users	-1.16	-1.28	+0.12	+1.16
Per Capita				
Diversion	-	-100.0%	9.2%	90.8%

Notes: This table presents results from an exercise where we simulate switching beneficiaries from facing the status quo formulary restrictions to facing prior authorization restrictions on all previously-unrestricted drugs. The first two panels detail the change in spending and utilization of all drug, restricted drugs (those drug-plan-region-year observations where an authorization restriction was in place in the status quo), unrestricted drugs, and no drug. In those panels, the upper row gives the percent change in these quantities, while the lower row presents the absolute change per beneficiary-year. The final panel details the share of beneficiaries moving away from restricted drugs to either unrestricted drugs or no drug .

Appendix Table A14: Per Capita Administrative Burden of Authorization Restrictions from Applying Authorization Restrictions to Currently-Unrestricted Drugs

		Request Rejection Rate				
		0%	1.5%	4%	7.5%	15%
Paperwork Cost	$11.62	$110.04	$111.72	$114.63	$118.96	$129.46
	$18.19	$172.26	$174.88	$179.44	$186.22	$202.66
	$21.72	$205.69	$208.82	$214.26	$222.36	$241.98
	$22.48	$212.88	$216.13	**$221.75**	$230.14	$250.45
	$31.30	$296.41	$300.92	$308.76	$320.44	$348.72
	$50	$473.50	$480.71	$493.22	$511.89	$557.05
	$100	$946.99	$961.41	$986.45	$1023.77	$1114.11
	$200	$1893.98	$1922.83	$1972.90	$2047.55	$2228.22

Notes: This table reports estimates of the increase in administrative costs from a simulation of switching beneficiaries from facing the status quo formulary restrictions to facing prior authorization restrictions on all previously-unrestricted drugs. Each cell represents the estimate under a calibrated set of values for the application cost a and rejection rate r.

Appendix Table A15: Spending Reductions per Administrative Dollar from Applying Authorization Restrictions to Currently-Unrestricted Drugs

		Request Rejection Rate				
		0%	1.5%	4%	7.5%	15%
Paperwork Cost	$11.62	1.65	1.63	1.58	1.53	1.40
	$18.19	1.05	1.04	1.01	0.97	0.90
	$21.72	0.88	0.87	0.85	0.82	0.75
	$22.48	0.85	0.84	**0.82**	0.79	0.72
	$31.30	0.61	0.60	0.59	0.57	0.52
	$50	0.38	0.38	0.37	0.35	0.33
	$100	0.19	0.19	0.18	0.18	0.16
	$200	0.10	0.09	0.09	0.09	0.08

Notes: This table reports estimates of the ratio of reductions in drug spending to the increase in administrative costs from a simulation of switching beneficiaries from facing the status quo formulary restrictions to facing prior authorization restrictions on all previously-unrestricted drugs. Each cell represents the estimate under a calibrated set of values for the application cost a and rejection rate r. Ratios above 1 indicate net financial savings, while ratios below 1 indicate net financial losses.

Appendix Table A16: Summary Statistics for LIS Transition Sample

	Analytic Sample
Avg. Age	70.4
Share Female	64.7
Share White	72.1
Avg. Elixhauser Index	3.36
Share With Any Drug Use	93.0
Avg. # Unique Drugs Taken	10.0
Avg. # Unique Drugs Taken with Authorization Restrictions	0.1
Avg. Drug Spending	$2,418
Avg. Non-Drug Medical Spending	$4,978
Beneficiary-year observations	956,460

Notes: This table provides summary statistics for the sample of beneficiaries who transition into the LIS program during our sample window. This is the primary sample used in Section 6.1.

Appendix Table A17: Summary Statistics for Oral Anticoagulant Sample

Mean Age	71.0
Share of female beneficiaries	63.5%
Share of white beneficiaries	61.8%
Mean $CHADS^2Vasc^2$ score	5.61
Share of anticoagulant users	29.1%
Share of NOAC users	4.33%
Share of Warfarin users	26.0%
Share of beneficiary-years facing prior auth on all NOACs	17.1%
Share of beneficiary-years facing prior auth on no NOACs	79.3%
Beneficiary-years	134,182

Notes: This table provides summary statistics for the sample of beneficiaries with prior diagnosis of atrial fibrillation, deep vein thrombosis, and/or pulmonary embolism. This is the primary sample used in Section 6.2.1.

C Prior Authorization Form Examples

https://providers.amerigroup.com

Novel Oral Anticoagulants Prior Authorization of Benefits Form

CONTAINS CONFIDENTIAL PATIENT INFORMATION
Complete form in its entirety and fax to: Prior Authorization of Benefits Center at 1-844-512-9004.
Provider Help Desk: 1-800-454-3730

1. Patient information	**2. Physician information**
Patient name:_____	Prescribing physician:_____
Patient ID #: _____	Physician address: _____
Patient DOB:_____	Physician phone #: _____
Date of Rx: _____	Physician fax #:_____
Patient phone #:_____	Physician specialty: _____
Patient email address: _____	Physician DEA: _____
	Physician NPI #: _____
	Physician email address: _____

3. Medication	**4. Strength**	**5. Directions**	**6. Quantity per 30 days**
_____	_____	_____	Specify: _____

7. Diagnosis:_____

8. Approval criteria: (Check all boxes that apply. Note: Any areas not filled out are considered not applicable to your patient and may affect the outcome of this request.)

Prior authorization (PA) is not required for preferred novel oral anticoagulants (NOACs). PA is required for nonpreferred NOACs. Requests for doses outside of the manufacturer recommended dose will not be considered. Payment will be considered for FDA approved or compendia indications under the following conditions:

1. Patient does not have a mechanical heart valve.
2. Patient does not have active bleeding.
3. For a diagnosis of atrial fibrillation or stroke prevention, patient has the presence of at least 1 additional risk factor for stroke, with a CHA_2DS_2-VASc score ≥1.
4. A recent creatinine clearance (CrCl) is provided.
5. A recent Child-Pugh score is provided.
6. Patient's current body weight is provided.
7. Patient has documentation of a trial and therapy failure at a therapeutic dose with at least two preferred NOACs.
8. For requests for edoxaban, documentation patient has had 5 to 10 days of initial therapy with a parenteral anticoagulant (low molecular weight heparin or unfractionated heparin). The required trials may be overridden when documented evidence is provided that the use of these agents would be medically contraindicated.

Preferred (no PA required if within established quantity limits)
☐ Eliquis ☐ Xarelto
☐ Pradaxa

Nonpreferred
☐ Savaysa

IAPEC-X1664-19 December 2019

OptumRx has partnered with CoverMyMeds to receive prior authorization requests, saving you time and often delivering real-time determinations.
Visit go.covermymeds.com/OptumRx to begin using this free service.
Please note: All information below is required to process this request.
Mon-Fri: 5am to 10pm Pacific / Sat: 6am to 3pm Pacific

Zetia® (ezetimibe) Prior Authorization Request Form

DO NOT COPY FOR FUTURE USE. FORMS ARE UPDATED FREQUENTLY AND MAY BE BARCODED

Member Information (required)			**Provider Information (required)**		
Member Name:			Provider Name:		
Insurance ID#:			NPI#:	Specialty:	
Date of Birth:			Office Phone:		
Street Address:			Office Fax:		
City:	State:	Zip:	Office Street Address:		
Phone:			City:	State:	Zip:

Medication Information (required)		
Medication Name:	Strength:	Dosage Form:
❑ Check if requesting **brand**	Directions for Use:	
❑ Check if request is for **continuation of therapy**		

Clinical Information (required)

Select the diagnosis below:
- ❑ Homozygous Familial Hypercholesterolemia (HoFH)
- ❑ Homozygous Sitosterolemia
- ❑ Primary Hypercholesterolemia
- ❑ Other diagnosis: _____ ICD-10 Code(s):_____

Clinical information:
Has the patient's diagnosis been confirmed? ❑ **Yes** ❑ **No**

Select the medications the patient has a failure, contraindication, or intolerance to:
- ❑ Ezetimibe-simvastatin
- ❑ Lovastatin
- ❑ Simvastatin
- ❑ Other statin or statin combination product. Please specify all: _____

Quantity limit requests:
What is the quantity requested per DAY? _____

What is the reason for exceeding the plan limitations?
- ❑ Titration or loading dose purposes
- ❑ Patient is on a dose-alternating schedule (e.g., one tablet in the morning and two tablets at night, one to two tablets at bedtime)
- ❑ Requested strength/dose is not commercially available
- ❑ Other: _____

Are there any other comments, diagnoses, symptoms, medications tried or failed, and/or any other information the physician feels is important to this review?

_____

_____

Please note: This request may be denied unless all required information is received.
For urgent or expedited requests please call 1-800-711-4555.
This form may be used for non-urgent requests and faxed to 1-800-527-0531.

ANTIPSYCHOTICS
PRIOR AUTHORIZATION FORM
(form effective 1/5/21)

Keystone First | PERFORMRX℠ Next Generation Pharmacy Benefits

Fax to PerformRx℠ at **1-215-937-5018**, or to speak to a representative call **1-800-588-6767**.

PRIOR AUTHORIZATION REQUEST INFORMATION

☐ New request ☐ Renewal request	Total pages:	Office contact/phone:	LTC facility contact/phone:

PATIENT INFORMATION

Patient name:	Patient ID#:	DOB:
Street address:	Apt #:	City/state/zip:

PRESCRIBER INFORMATION

Prescriber name:		
Specialty:	NPI:	State license #:
Street address:	Suite #:	City/state/zip:
Phone:	Fax:	

MEDICATION REQUESTED

Preferred Agents

☐ Abilify Maintena	☐ fluphenazine elixir	☐ haloperidol tablet	☐ Invega Sustenna	☐ Perseris ER injection	☐ risperidone tablet
☐ aripiprazole tablet	☐ fluphenazine oral concentrate	☐ haloperidol decanoate inj	☐ Invega Trinza	☐ quetiapine tablet	☐ trifluoperazine tablet
☐ Aristada ER injection	☐ fluphenazine tablet	☐ haloperidol lactate inj.	☐ loxapine capsule	☐ quetiapine ER tablet	☐ ziprasidone capsule
☐ Aristada Initio injection	☐ fluphenazine decan. inj.	☐ haloperidol lactate oral concentrate	☐ olanzapine tablet	☐ Risperdal Consta	☐ Zyprexa Relprevv
☐ clozapine tablet	☐ Haldol injection		☐ perphenazine tablet	☐ risperidone solution	

Non-Preferred Agents

☐ Abilify Mycite	☐ chlorpromazine tablet	☐ Geodon injection	☐ olanzapine inj/ODT	☐ Saphris SL tablet	☐ Versacloz suspension
☐ Abilify tablet	☐ clozapine ODT	☐ Haldol decanoate inj.	☐ olanzapine/fluoxetine cap	☐ Secuado patch	☐ Vraylar capsule
☐ Adasuve inhalation	☐ Clozaril tablet	☐ Invega ER tablet	☐ paliperidone ER tab	☐ Seroquel tablet	☐ Zyprexa tablet/injection
☐ amitriptyline/perphenazine	☐ Fanapt tablet	☐ Latuda tablet	☐ pimozide tablet	☐ Seroquel XR tablet	☐ Zyprexa Zydis
☐ aripiprazole ODT	☐ Fazaclo dispersible tablet	☐ molindone tablet	☐ Rexulti tablet	☐ Symbyax capsule	☐ other:
☐ aripiprazole solution	☐ fluphenazine HCl injection	☐ Nuplazid capsule	☐ Risperdal solution/tablet	☐ thioridazine tablet	
☐ Caplyta capsules	☐ Geodon capsule	☐ Nuplazid tablet	☐ risperidone ODT	☐ thiothixene capsule	

Strength:	Dosage form:	Directions:	Quantity:	Refills:
Diagnosis:			Diagnosis code (required):	

PHARMACY INFORMATION (Prescriber to identify the pharmacy that is to dispense the medication):

Deliver to: ☐ Patient's Home ☐ Physician's Office ☐ Patient's Preferred Pharmacy Name:	
Pharmacy Phone #:	Pharmacy Fax #:
☐ I acknowledge that the patient agrees with the pharmacy chosen for delivery of this medication.	

REQUEST FOR A NON-PREFERRED AGENT

1. Has the patient taken the requested non-preferred antipsychotic in the past 90 days?
   ☐ Yes – *Submit documentation.* ☐ No
2. Has the patient tried and failed the preferred medications (listed above)?
   ☐ Yes – List medications tried: ☐ No
3. Does the patient have a contraindication or intolerance to the preferred medications?
   ☐ Yes – *Submit documentation of contraindication/intolerance.* ☐ No
4. **For oral Invega/paliperidone ER requests, does the patient have active liver disease with elevated LFTs or is the patient at risk for active liver disease?**
   ☐ Yes – *Submit documentation and lab values.* ☐ No

REQUEST FOR A PATIENT LESS THAN 18 YEARS OF AGE

5. Is this request for a dose increase of a previously approved medication? ☐ Yes – *Submit recent chart documentation supporting the increased dose.* ☐ No
6. Is the requested agent prescribed by, or in consultation with, one of the following physician specialists? ☐ Yes ☐ No *Submit documentation of consultation, if applicable.*
   ☐ child development pediatrician ☐ child & adolescent psychiatrist ☐ general psychiatrist (only if patient is ≥ 14 years of age) ☐ pediatric neurologist
7. Does the patient have severe behavioral problems related to a psychotic or neuro-developmental disorder? ☐ Yes – *Submit medical record documentation.* ☐ No
8. Has the patient tried non-drug therapies? ☐ Yes – *Submit medical record documentation.* ☐ No
9. Has the patient had the following baseline and/or follow-up monitoring? Check all that apply. ☐ BMI (or weight/height) ☐ blood pressure ☐ fasting glucose level ☐ fasting lipid panel
   ☐ presence of extrapyramidal symptoms (EPS) using the Abnormal Involuntary Movement Scale (AIMS)
   Submit documentation of all monitoring/test results.

REQUEST FOR A LOW-DOSE ORAL ANTIPSYCHOTIC FOR A PATIENT 18 YEARS OF AGE OR OLDER

10. What is the TOTAL daily dose of the requested medication? _____mg/day
    Submit documentation of complete medication regimen.
11. Is the low dose prescribed as part of a plan to titrate up to a therapeutic dose? ☐ Yes – *Submit documentation of titration plan.* ☐ No

REQUEST FOR THERAPEUTIC DUPLICATION OF AN ATYPICAL OR TYPICAL ANTIPSYCHOTIC

12. Does the patient have a medical reason for concomitant use of the requested medications? ☐ Yes – *Submit documentation with justification.* ☐ No
13. Is this request for a drug that is being titrated to, or tapered from, a drug in the same class? ☐ Yes – *List medication.* ☐ No

PLEASE FAX COMPLETED FORM WITH REQUIRED CLINICAL DOCUMENTATION

Prescriber signature:	Date:

KF_201073500-7

D Demand Estimation: Additional Details

To overcome computational hurdles, we estimate our nested demand system in Section 4 with a Poisson pseudo-maximum-likelihood estimation approach. This appendix describes 1) the justification for doing so and the estimation routine; and 3) the data processing required to make the data ready for estimation.

D.1 Estimating Nested Logit Demand Systems with Poisson Regression

We build on the equivalence of the likelihood functions of conditional multinomial logit estimation and Poisson regression. Readers interested in a deeper dive are encouraged to read Guimarães et al. (2003) and the references contained therein. That paper derives the equivalence between the two. We will instead briefly walk through the intuition.

Consider a conditional logit demand system for individuals i choosing a single good d from a choice set D. Individuals choose a good to maximize utility $u_{id} = \beta X_{id} + \epsilon_{id}$ for observed X_{id}. If ϵ is i.i.d. standard Gumbel distributed, then the probability that i chooses d is

$$P_{id} = \frac{\exp(\beta X_{id})}{\sum_{k \in D} \exp(\beta X_{ik})}$$

The sample analogue is c_{id}, the choice indicator vector which is 1 if i chose d and 0 otherwise. Typical estimation involves noting that, with conditional logit demand, $E[c_{id}] = P_{id}$, and rewriting this as a maximum likelihood problem. However, note that if we assert this equality and take logs of both sides, we have

$$\log\left(E[c_{id}]\right) = \beta X_{id} - \underbrace{\log\left[\sum_{k \in D} \exp(\beta X_{ik})\right]}_{\alpha_i} \tag{4}$$

with the term α_i as a quantity that is constant across all goods within an individual. This is equivalent to the typical Poisson regression formulation, and therefore the coefficient β on X_{id} from an individual-level conditional logit can be estimated with an individual-product-level Poisson regression that includes X_{id} and individual-level fixed effects.

Further, imagine that instead of individual-level choices, we observe group-level market shares s_{gd} for a group of individuals g where $X_{id} = X_{i'd} = X_{gd}$ for all d and for all $i, i' \in g$. Note that $E[s_{gd}] = P_{gd}$, and so a group-level Poisson regression as formulated above will equivalently estimate β.

The classic alternative to this is the approach of Berry (1994). He notes that if one takes Equation 4 and difference out the expression for a reference good 0, one gets

$$\log\left(E[s_{gd}]\right) - \log\left(E[s_{g0}]\right) = \beta(X_{gd} - X_{g0})$$

and if one assumes that the Law of Large Numbers applies, then the observed shares $\hat{s}_{gd}$ are approximately equal to their expectations, $E[s_{gd}]$, and the econometrician can run a regression of the log share difference between the focal good and the reference good $(\log(\hat{s}_{gd}) - \log(\hat{s}_{g0}))$ on the difference in characteristics

between them (and since the reference good is often an outside good with all characteristics set to zero, the regressors can simply be the characteristics of the focal good). These approaches are analogous. Berry's approach differences out the α_i from Equation 4.

The difficulty with this approach arises in finite samples, in two ways. First, the Berry approach will be biased in finite samples where $\hat{s}_{gd} \not\approx E[s_{gd}]$ and thus Jensen's inequality ensures that $E[\log(\hat{s}_{gd})] \not\approx \log\left(E[s_{gd}]\right)$; the bias will be larger when this approximation is poorer: in smaller samples and/or when groups are smaller. Second, and more importantly in our application, in finite samples, as $P_{gd} \to 0$ for a good j, the probability of observing market shares of zero for that good becomes nontrivial. Indeed, in our setting, 98.7% of beneficiary-drug pairs have zero usage. In that case, $\log(\hat{s}_{gd})$ is undefined. In contrast, the Poisson regression approach is not biased in finite samples and can accept market share observations of zero.[42]

In Section 4, we want to estimate a nested logit model rather than a conditional logit model, with a single nest incorporating all drug options, excluding the option of taking no drug. As a reminder, the utility function for the nested logit is:

$$u_{idt} = \underbrace{\beta_C \text{Auth}_{idt} + \delta_C \text{Excl}_{idt} + \kappa_{dm(it)}}_{V_{idt}} + \xi_{iC}\mathbf{1}\{d \neq 0\} + \lambda\epsilon_{idt}$$

where ϵ_{idt} and $\xi_{iC}\mathbf{1}\{d \neq 0\} + \lambda\epsilon_{idt}$ are Gumbel distributed and the choice probabilities are

$$P_{idt} = \underbrace{\frac{\exp\frac{V_{idt}}{\lambda_C}}{\sum_{k\in C}\exp\frac{V_{ikt}}{\lambda_C}}}_{P_{id}|d\neq 0} \times \underbrace{\frac{\left(\sum_{k\in C}\exp\frac{V_{ikt}}{\lambda_C}\right)^{\lambda_C}}{1+\left(\sum_{k\in C}\exp\frac{V_{ikt}}{\lambda_C}\right)^{\lambda_C}}}_{P_{i(d\neq 0)}}$$

for inside goods with V_{idt} as the mean utility of good d for individual i in time t, and

$$P_{i0t} = \frac{1}{1+\left(\sum_{k\in C}\exp\frac{V_{ikt}}{\lambda_C}\right)^{\lambda_C}}$$

for the outside good.

Berry (1994) shows that the nested logit demand system can be estimated via log-linear OLS by including $\log(s_{gd}/s_{g(d\neq 0)})$ as an additional regressor, with its estimated coefficient being equal to $1-\lambda_C$. However, in settings where s_{gd} is zero, this regressor will be undefined. Therefore, we cannot use this approach. Instead, we estimate this model using a two-step approach: First, we estimate all of the mean utility parameters using the drug choice; then, we estimate λ_C using the choice of whether to consume a drug at all or not.[43]

Specifically, we note that the nested logit utility can be divided by λ_C to get

[42] Additionally, the Berry approach cannot be used on individual-level data, since the outcome variable will take on the value of zero for non-chosen goods.

[43] Train (2009) notes that this form of estimation is consistent but inefficient, since the across-nest choice is not incorporated into the estimation of the within-nest choice. In our case, since the across-nest choice only incorporates one additional alternative, which inherently cannot face prior authorization or exclusion, the two-step approach is unlikely to cause significant efficiency loss.

$$\underbrace{\frac{u_{idt}}{\lambda_C}}_{\tilde{u}_{idt}} = \underbrace{\frac{\beta_C}{\lambda_C}}_{\tilde{\beta}_C} \text{Auth}_{idt} + \underbrace{\frac{\delta_C}{\lambda_C}}_{\tilde{\delta}_C} \text{Excl}_{idt} + \underbrace{\frac{\kappa_{dm(it)}}{\lambda_C}}_{\tilde{\kappa}_{dm(it)}} + \frac{\xi_{iC}\mathbf{1}\{d \neq 0\}}{\lambda_C} + \epsilon_{idt}$$

Additionally, if we define a reference inside good, good 1, we can rewrite the above as

$$\tilde{u}_{idt} = \tilde{\beta}_C \text{Auth}_{idt} + \tilde{\delta}_C \text{Excl}_{idt} + \underbrace{(\tilde{\kappa}_{dm(it)} - \tilde{\kappa}_{1m(it)})}_{\tilde{\Delta}\kappa_{dm(it)}} + \tilde{\kappa}_{1m(it)} + \epsilon_{idt}$$

Since $\tilde{u}$ is a monotonic transformation of u, maximizing u is equivalent to maximizing $\tilde{u}$; additionally, since ϵ is standard Gumbel, then the probability of choosing d conditional on choosing an inside good (and conditional on a draw of ξ_{iC}) is

$$P_{id|d\neq 0} = \frac{\exp \frac{V_{idt}}{\lambda_C}}{\sum_{k\in C} \exp \frac{V_{ikt}}{\lambda_C}} = \frac{\exp\left(\tilde{V}_{idt} + \tilde{\kappa}_{1m(it)} + \frac{\xi_{iC}\mathbf{1}\{d\neq 0\}}{\lambda_C}\right)}{\sum_{k\neq 0} \exp\left(\tilde{V}_{ikt} + \tilde{\kappa}_{1m(it)} + \frac{\xi_{iC}\mathbf{1}\{d\neq 0\}}{\lambda_C}\right)} = \frac{\exp(\tilde{V}_{idt})}{\sum_{k\neq 0}\exp(\tilde{V}_{ikt})}$$

with $\tilde{V}_{idt} = \tilde{\beta}_C \text{Auth}_{idt} + \tilde{\delta}_C \text{Excl}_{idt} + \tilde{\Delta}\kappa_{dm(it)}$, and the third equality coming from the fact that $\tilde{\kappa}_{1m(it)}$ and $\frac{\xi_{iC}\mathbf{1}\{d\neq 0\}}{\lambda_C}$ are common to all inside goods and thus have no effect on choice probabilities.

The key factor here is that within a nest, the choice probabilities are standard logit and so can be treated as such. Moreover, since all of the remaining regressors are defined at the group level, we can estimate the group-drug-year-level Poisson regression:

$$\log\left(E[s_{gdt}]\right) = \tilde{\beta}_C \text{Auth}_{gdt} + \tilde{\delta}_C \text{Excl}_{gdt} + \tilde{\Delta}\kappa_{dm(it)} + \alpha_{gt}$$

where we regress group-drug-year-level market shares on dummies for prior authorization and exclusion, with drug-market and group-year fixed effects. This gives us estimates, $\hat{\tilde{\beta}}, \hat{\tilde{\delta}}$, and $\hat{\tilde{\Delta}}\kappa$, with α_{gt} as nuisance parameters.

We then have two remaining unknown parameters: λ_C and $\tilde{\kappa}_{1m(it)}$. Noting again that $\frac{V_{idt}}{\lambda} = \tilde{V}_{idt} + \tilde{\kappa}_{1m(it)}$, the probability of a member of g choosing any drug (compared to no drug) is

$$P_{g(d\neq 0)} = \frac{\left(\sum_{k\in C} \exp \frac{V_{gkt}}{\lambda_C}\right)^{\lambda_C}}{1 + \left(\sum_{k\in C} \exp \frac{V_{gkt}}{\lambda_C}\right)^{\lambda_C}} = \frac{\left(\sum_{k\neq 0} \exp(\tilde{V}_{gkt} + \tilde{\kappa}_{1m(gt)})\right)^{\lambda_C}}{1 + \left(\sum_{k\neq 0} \exp(\tilde{V}_{gkt} + \tilde{\kappa}_{1m(gt)})\right)^{\lambda_C}}$$

Taking the log of both sides, we see that

$$\log P_{i(d\neq 0)t} = \kappa_{1m(gt)} + \lambda_C \hat{\mathcal{V}}_{gt} + \omega_{gt}$$

with $\hat{\mathcal{V}}_{gt} = \log\left(\sum_{k\neq 0} \exp(\hat{\tilde{V}}_{gdt})\right)$, the inclusive value of the inside goods, and a group fixed effect $\omega_{gt} = -\log\left(1 + \left(\sum_{k\neq 0} \exp(\tilde{V}_{gdt} + \tilde{\kappa}_{1m(gt)})\right)^{\lambda_C}\right)$. Additionally, the choice probability of the outside good (no drug) is

$$\log P_{g(d\neq 0)} = \omega_g$$

Therefore, we can estimate $\kappa_{1m(gt)}$ and λ_C by running a Poisson regression at the group-option-year level, with options being either taking any drug or taking no drug; with the outcomes as group market shares, and the regressors being a market-level intercept for the 'any drug' option, the inclusive value $\mathcal{V}$ interacted with an indicator for the 'any drug' option, and group-class-year fixed effects. Once we have done this, all relevant parameters have been estimated.[44]

D.1.1 Instrumental Variable Estimation

Our approach requires us to instrument for the prior authorization and exclusion status of a drug in the plan the beneficiary was *enrolled in* with the same from the plan they were *assigned to*. Instrumental variables approaches are tricky in nonlinear estimation. We use the control function approach of Petrin and Train (2010). This is further complicated by the fact that we estimate our model in two stages, both of which require a control function at each stage.

To estimate the inner nest choice (i.e., the choice of drug conditional on choosing any drug), we first run the regression:

$$\begin{bmatrix} \text{Auth}_{idt}^{\text{Enrolled}} \\ \text{Excl}_{idt}^{\text{Enrolled}} \end{bmatrix} = \vec{\gamma}^1 \begin{bmatrix} \text{Auth}_{idt}^{\text{Assigned}} \\ \text{Excl}_{idt}^{\text{Assigned}} \end{bmatrix} + \vec{K}_{dm(it)} + \vec{u}_{idt}^1$$

i.e., a linear regression of dummies for formulary status in the enrolled plan on the same dummies in the assigned plan, plus drug-market fixed effects. We can then recover the estimated residuals,

$$\hat{\vec{u}}_{idt}^1 = \begin{bmatrix} \text{Auth}_{idt}^{\text{Enrolled}} \\ \text{Excl}_{idt}^{\text{Enrolled}} \end{bmatrix} - \left(\hat{\vec{\gamma}}^1 \begin{bmatrix} \text{Auth}_{idt}^{\text{Assigned}} \\ \text{Excl}_{idt}^{\text{Assigned}} \end{bmatrix} + \hat{\vec{K}}_{dm(it)}^1 \right)$$

and include them as a control in the Poisson regression on drug choice market shares.

For the outer choice model (the choice of drug or no drug), we must also account for endogeneity: specifically, the endogeneity of the inclusive value $\mathcal{V}$, which governs the inclusive value of the formulary the beneficiary faces. To account for this, we run the following regression:

$$\mathcal{V}_{it}^{\text{Enrolled}} = \gamma^2 \mathcal{V}_{it}^{\text{Assigned}} + K_{1m(it)} + u_{it}^2$$

the linear regression of the inclusive value estimated for the plan of enrollment on the inclusive value of the plan of assignment (only having an effect for the 'any drug' choice), with a market-level fixed effect.

We can then construct the estimated residuals from this regression,

$$\hat{u}_{idt}^2 = \mathcal{V}_{jt}^{\text{Enrolled}} - \left(\hat{\gamma}^2 \mathcal{V}_{jt}^{\text{Assigned}} + \hat{K}_{1m(it)} \right)$$

and use those as controls in the Poisson regression on the shares that choose any drug.

[44] While we only estimated versions of β, γ, and $\Delta\kappa$ that were normalized by λ, the normalized parameters are sufficient to compute counterfactual simulations. They can be retransformed back into their non-normalized forms if need be.

The control function approach allows us to control for the extent of deviation of beneficaries away from their assigned formulary. The coefficient on the residuals from the 'first stage' in the choice model capture the extent to which beneficiaries who endogenously select into plans with different coverage than their default do so because they prefer specific drugs that they are deviating to fill more easily.

One feature of this approach is that the largest group of beneficiaries that can be constructed with modeled homogeneity within the group is at the enrolled-plan-by-assigned-plan level; therefore, this is the group g that we use.

D.1.2 Estimation Routine

To summarize, our procedure is, for each therapeutic class:

1. Restrict to only inside good options (i.e., exclude beneficiaries in a plan who took no drug in the class), and construct a dataset of group-year drug choice shares for drugs within the class, where groups are enrolled-plan-by-assigned-plan pairs.

2. Run the 'inner choice first stage' linear regression of dummies for formulary status in the enrolled plan on dummies for formulary status in the assigned plan and drug-market fixed effects:

$$\begin{bmatrix} \text{Auth}_{gdt}^{\text{Enrolled}} \\ \text{Excl}_{gdt}^{\text{Enrolled}} \end{bmatrix} = \vec{\gamma}_C^1 \begin{bmatrix} \text{Auth}_{gdt}^{\text{Assigned}} \\ \text{Excl}_{gdt}^{\text{Assigned}} \end{bmatrix} + \vec{K}_{dm(gt)} + \vec{u}_{gdt}^1$$

   to estimate the group-by-drug-by-year residuals $\hat{\vec{u}}_{gdt}^1$.

3. Run the 'inner choice second stage' Poisson regression of group-year drug choice shares on dummies for the prior authorization and exclusion status of the drug in the *enrolled* plan, drug-market fixed effects, plan-year fixed effects, and the estimated residuals from above:

$$\log(E[s_{gdt}]) = \beta_C \text{Auth}_{gdt}^{\text{Enrolled}} + \delta_C \text{Excl}_{gdt}^{\text{Enrolled}} + \Delta\kappa_{dm(gt)} + \alpha_{gt} + \zeta_C^1 \hat{\vec{u}}_{gdt}^1$$

4. Take the estimated parameters β_C, δ_C, and $\Delta\kappa_{dm(gt)}$, and use them to construct the inclusive values $\mathcal{V}$ for all plans in every year.

5. Construct a dataset with two observations for each plan-year, one containing the share of beneficiaries taking any drug in the class, the other containing the share of beneficiaries taking no drug in the class.

6. Run the 'outer choice first stage' linear regression of the inclusive value for the plan the beneficiary enrolled in on the inclusive value for the plan they were assigned to, plus a market fixed effect interacted with a dummy indicating the 'any drug' choice:

$$\mathcal{V}_{gt}^{\text{Enrolled}} = \gamma^2 \mathcal{V}_{gt}^{\text{Assigned}} + K_{1m(gt)} + u_{gt}^2$$

   to estimate the group-by-choice-by-year residuals $\hat{u}_{gdt}^2$.

7. Run the 'outer choice second stage' Poisson regression of group-year choice shares (drug or no drug) on the inclusive value of the enrolled plan, a market fixed effect, and the residuals estimated in the prior step, all interacted with a dummy indicating the 'any drug' choice, as well as a group-year fixed effect:

$$\log(E[s_{gDt}]) = \left[\lambda_C \mathcal{V}_{gt}^{\text{Enrolled}} + \kappa_{1m(gt)} + \zeta_C^2 \hat{u}_{gt}^2\right] \times \mathbf{1}\{D = 1\} + \omega_{gt}$$

where $D = 0$ reflects "no drug" and $D = 1$ reflects "any drug."

This approach makes clear how λ_C is identified, and how it reflects the extent of intensive vs. extensive margin substitution. The components of $\mathcal{V}_{gt}$ are identical across groups g within a region and year *except* for the formularies they face; the demand parameters are otherwise identical. λ_C is identified from the extent to which plans with more stringent formularies characterized by greater use of prior authorization and exclusion (and thus lower inclusive values) have less use of any drug. When λ_C is close to zero, only intensive margin substitution matters: When beneficiaries are deterred from one drug, they will substitute to another, leaving the share of beneficiaries taking any drug constant. In contrast, when λ_C is close to one, beneficiaries will substitute to other options proportionally, and thus most beneficiaries who are deterred from a drug will move to no drug.

To estimate the Poisson regressions, we use the Poisson pseudo-maximum-likelihood estimation method developed by Correia et al. (2020) that allows for fast estimation of Poisson regression models with high-dimensional fixed effects. For ease of computation, we estimate this model separately for each therapeutic class.

D.2 Standard Errors

Since our estimation procedure has multiple steps, and we want our standard errors to incorporate the variation in estimators that can come from noise in any particular step, the ideal is to bootstrap the entire procedure described above. However, our estimation procedure relies on many fixed effects which are sparsely estimated, i.e., the number of observations pinning down the fixed effect is quite small. This is especially true with many of our drug-market-year fixed effects. If we cannot observe any individual taking the drug in that market-year, we will be forced to estimate the fixed effect at $-\infty$. With a standard bootstrap, the odds of this occurring for any given drug-market-year are nontrivial. This will cause our confidence intervals to necessarily be too large for some estimators, driven by computational issues rather than true variation.

Instead, we use the Bayesian bootstrap (Shao and Tu 1995).[45] Instead of resampling units with replacement, we instead, for each unit, draw random weights at each bootstrap run, and re-estimate the model with these weights applied. The distribution of parameter estimates from each run serves as our estimated sampling distribution of the parameter. That work suggests that an appropriate weight for each individual can be drawn from the exponential distribution with scale parameter 1. To speed up computation, we draw this at the group-by-drug-by-year level rather than the individual-by-year level, which we can do since the sum

[45] We thank Peter Hull for alerting us to the Bayesian bootstrap's suitability for this purpose.

of exponentially-distributed random variables has a Gamma distribution. If n individuals from group g in year t were observed, the appropriate weight is $w_{gt} \sim \text{Gamma}(n, 1)$.[46]

For each therapeutic-class-specific drug demand estimation routine, we replace the Poisson pseudo-maximum-likelihood method with a **weighted** psuedo-maximum-likelihood estimator, using the drawn weights. We use 500 bootstrap runs, and preserve the weights within a run across classes, so that within a given bootstrap run, the same weights are being used to compute therapeutic-class-level market shares and spending and thus correctly aggregate across classes. Standard errors for a parameter (or function of a set of parameters) are estimated as the standard deviation of that parameter over the 500 estimated bootstrap runs.

D.3 Data Processing for Demand Estimation

Since we take a discrete choice approach to modeling drug demand, estimating such a model requires data formatted as a discrete choice. However, since our analysis is at the level of a year, this is naturally often violated: A patient may take multiple drugs in a given year, especially to satisfy step therapy requirements. In the first column of Appendix Table A18, we report the share of beneficiaries who took multiple drugs in a given year within a class (conditional on taking at least one drug). Across classes, this averages to 15.1% of beneficiaries, but ranges from 0% to 51.8%. To transform this into an appropriate dataset, we pick, for each beneficiary-year, the modal drug within the class they took that year (as defined by the drug consumed with the most days supply, breaking ties randomly), and assign that as their 'chosen' drug for the year. Column two of Appendix Table A18 reports, for each class of the top 30 by gross spending, the share of days supply that the assigned drug made up across beneficiary-year pairs who filled multiple drugs within a class for a year. Appendix Figure A8 plots the distribution of this multiple-drug-user share across classes. On average, across all classes, the assigned drug made up 63.9% of days supply for these beneficiaries and 90% for all beneficiaries. Appendix Figures A9 and A10 plot the distributions of these values across classes.

The identification of all of our demand parameters requires that any market (region-year) in a particular class must have at least one drug that faces prior authorization in at least one (but not all) plans in that market; otherwise, β cannot be identified from behavior in that market. Additionally, in a similar vein, it must be true that at least two drugs are ever taken; if not, β is not identified separately from λ, since both will influence inside drug vs. no drug choice.

In the third and fourth columns of Appendix Table A18, we list the share of markets that violate at least one of the two above requirements (both as a share of market-years and weighted by beneficiary counts) for the top 30 therapeutic classes by spending. In Appendix Figures A11 and A12, we plot the distribution of the unweighted and weighted shares. A sizable number of classes have very high shares of markets that do not contribute to identification. In testing, these classes tended to be ones where β was estimated with the wrong sign (i.e., we estimated that, for that class, prior authorization *increased* use of a focal drug), and ones where λ was estimated at values well outside the $[0, 1]$ interval that we would expect it to lie on. We therefore decide to only use classes where no more than 10% of markets violate at least one of the two requirements.

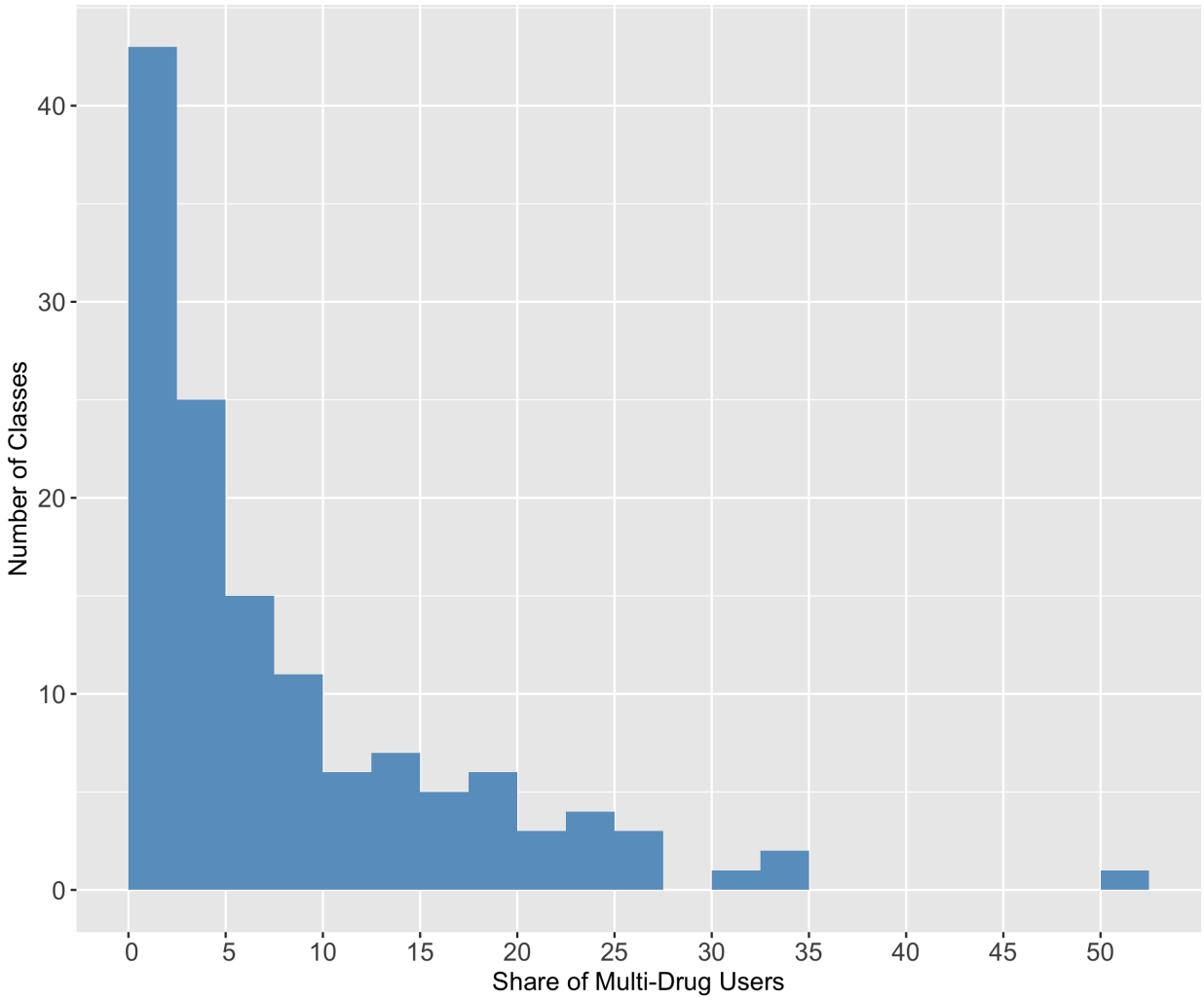
[46] Note that the expected value of w_{gt} is n, which is the expected number of times one would draw a member from the group in a standard bootstrap approach.

Appendix Table A18: Class Level Nested Logit Summary Statistics for Top 30 Classes by Part D Spending

Class	Unweighted Market Survival	Weighted Market Survival	Share of Focal Days Supply, Multiple Drug Users	Share of Multiple Drug Users
Antihyperlipidemic Drugs, NEC	94.3%	98.7%	59.5%	23.9%
Psychother,Tranq/Antipsychotic	95.2%	99.0%	60.4%	31.9%
Antidiabetic Agents, Insulins	95.7%	99.1%	60.8%	51.8%
Gastrointestinal Drug Misc,NEC	97.1%	99.3%	72.8%	22.3%
Antivirals, NEC	89.5%	98.4%	36.6%	25.5%
Antidiabetic Agents, Misc	96.7%	99.3%	57.5%	25.5%
Antineoplastic Agents, NEC	92.9%	99.1%	67.3%	6.6%
Biological Response Modifiers	79.5%	96.7%	72.5%	4.1%
CNS Agents, Misc.	97.1%	99.3%	61.8%	10.5%
Psychother, Antidepressants	97.1%	99.2%	58.8%	32.6%
Adrenals & Comb, NEC	95.2%	99.0%	78.9%	25.9%
Analg/Antipyr, Opiate Agonists	94.3%	99.1%	66.3%	24.0%
Cardiac Drugs, NEC	96.2%	99.3%	73.0%	20.2%
Antiplatelet Agents, NEC	81.4%	94.8%	63.2%	12.5%
Immunosuppressants, NEC	91.0%	98.5%	61.9%	15.4%
Misc Therapeutic Agents, NEC	95.2%	99.1%	59.8%	24.8%
Anticonvulsants, Misc	91.4%	98.8%	57.0%	19.0%
Cardiac, Calcium Channel	93.8%	98.6%	71.6%	10.5%
Coag/Anticoag, Anticoagulants	88.6%	95.6%	85.5%	15.7%
Cardiac, Beta Blockers	90.0%	98.6%	71.9%	7.2%
Parasympathomimetic, NEC	84.3%	95.6%	72.2%	7.0%
Eye/Ear/Nose/Throat Misc, NEC	90.5%	98.7%	53.7%	35.0%
Analg/Antipyr,Nonstr/Antiinflm	96.2%	99.2%	71.1%	22.2%
Muscle Rel,Smooth-Genitour NEC	95.7%	99.2%	74.7%	15.3%
Antiinflam Agents EENT, NEC	96.7%	99.3%	67.2%	18.7%
Sympathomimetic Agents, NEC	92.9%	99.0%	73.4%	8.7%
Estrogens & Comb, NEC	90.0%	97.8%	74.4%	7.9%
Vasodilating Agents, NEC	71.0%	93.0%	79.1%	18.5%
Phosphorus Removing Agents,NEC	73.3%	94.1%	68.8%	7.9%
Cardiac, ACE Inhibitors	70.0%	90.5%	72.3%	5.3%

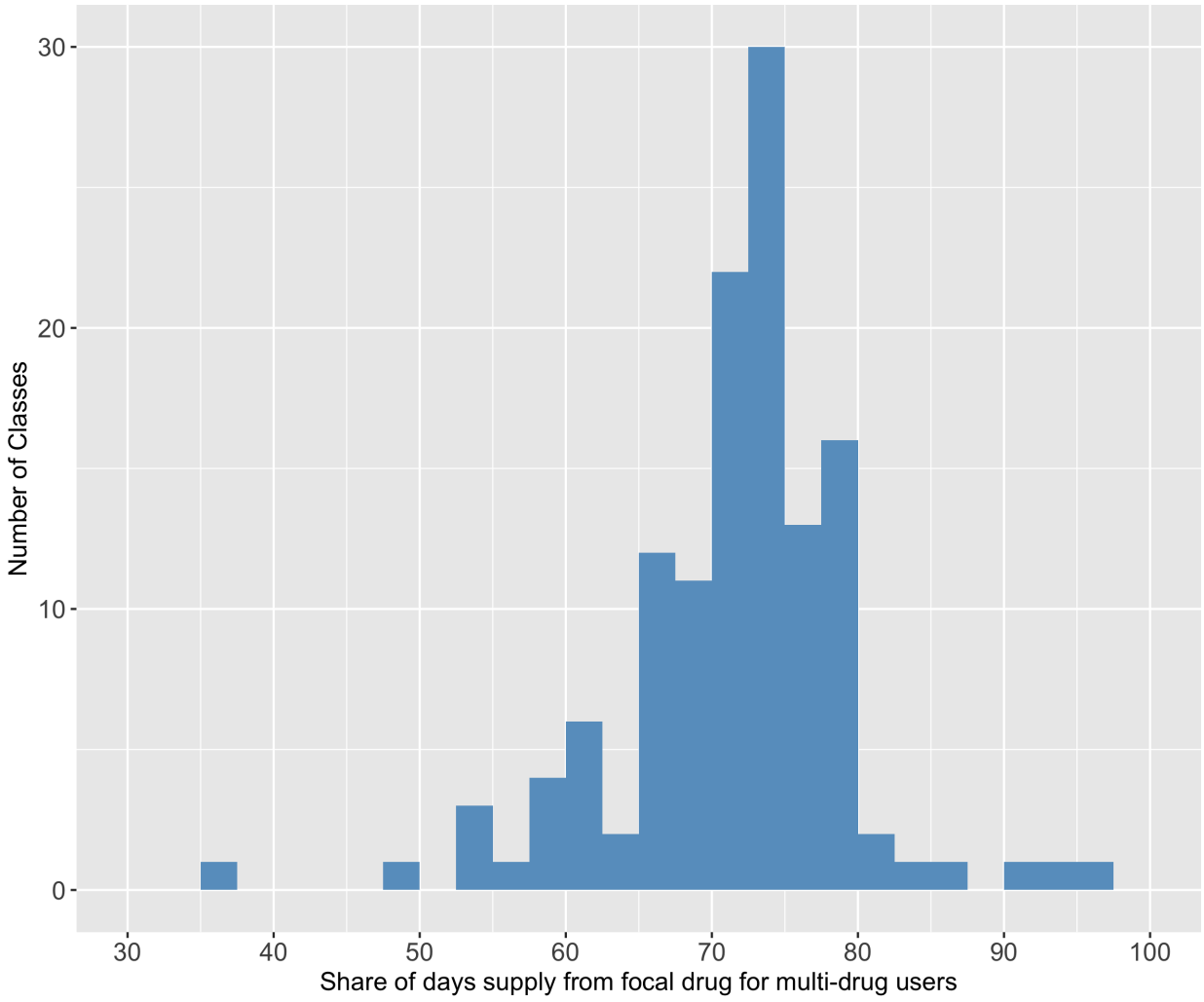
Notes: For each class listed, this table displays the share of markets (region-year pairs) that have (1) at least one drug in the class that is under a prior authorization restriction in between 0 and 100% of plans; and (2) where at least two drugs in the class are filled. The first and second columns give this statistic, the second weighted by beneficiary count within our sample. The fourth column lists the share of beneficiary-years who fill at least two drugs within the class in a given year, out of those who fill at least one drug. The third column lists the share of days supply made up by the most-used drug in the class, for this subpopulation of beneficiaries. Table is sorted by total Part D spending within our sample.

Appendix Figure A8: Share of Drug-Users Whom Take Multiple Drugs



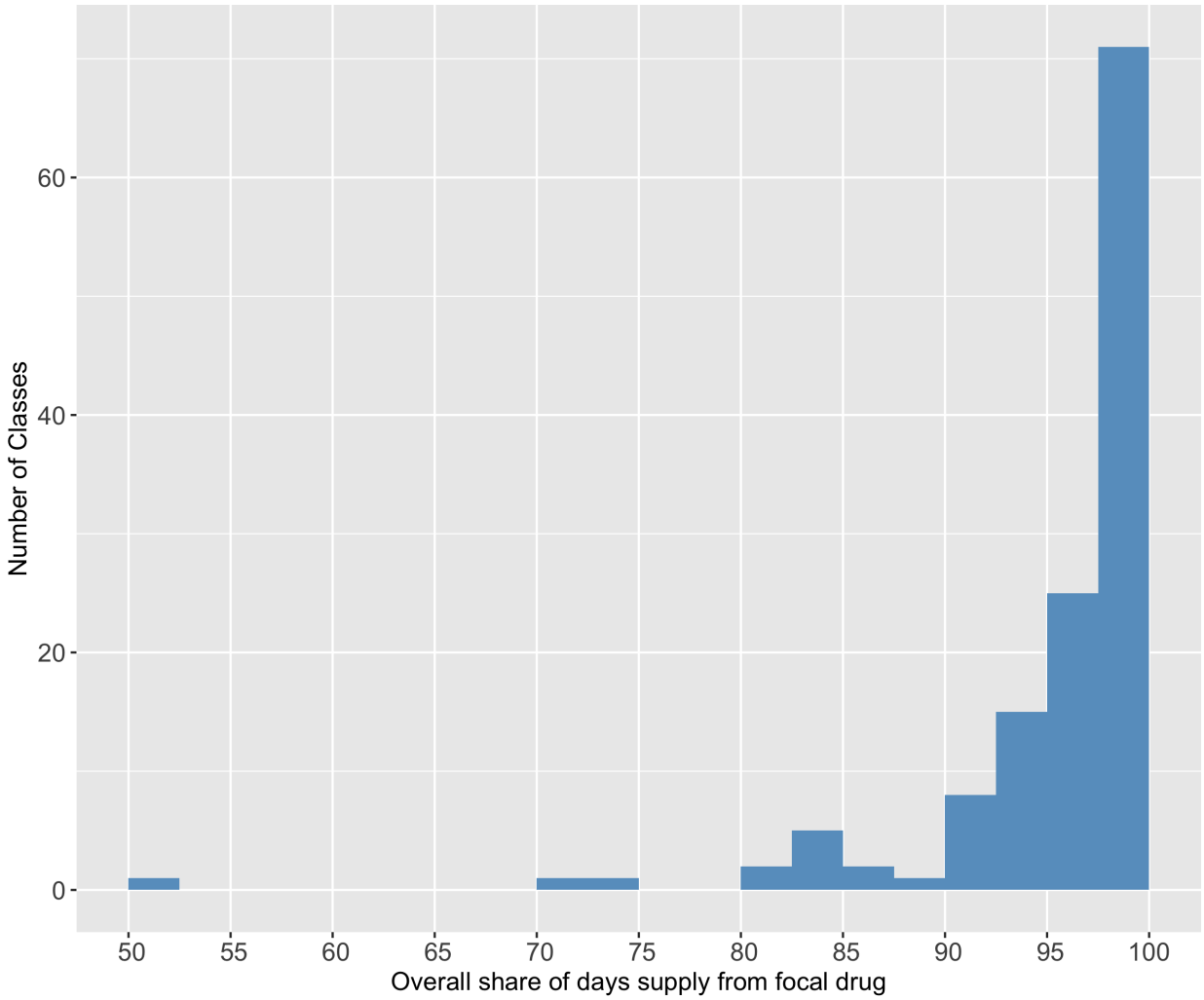
Notes: For each therapeutic class, we measure, out of the set of beneficiary-year pairs where the beneficiary took at least one drug within the class in that year, how many beneficiary-year pairs were ones in which the beneficiary took at least two drugs in the class. This figure plots the distribution of that statistic across classes.

Appendix Figure A9: Focal Drug Days Supply Share for Multi-Drug Users



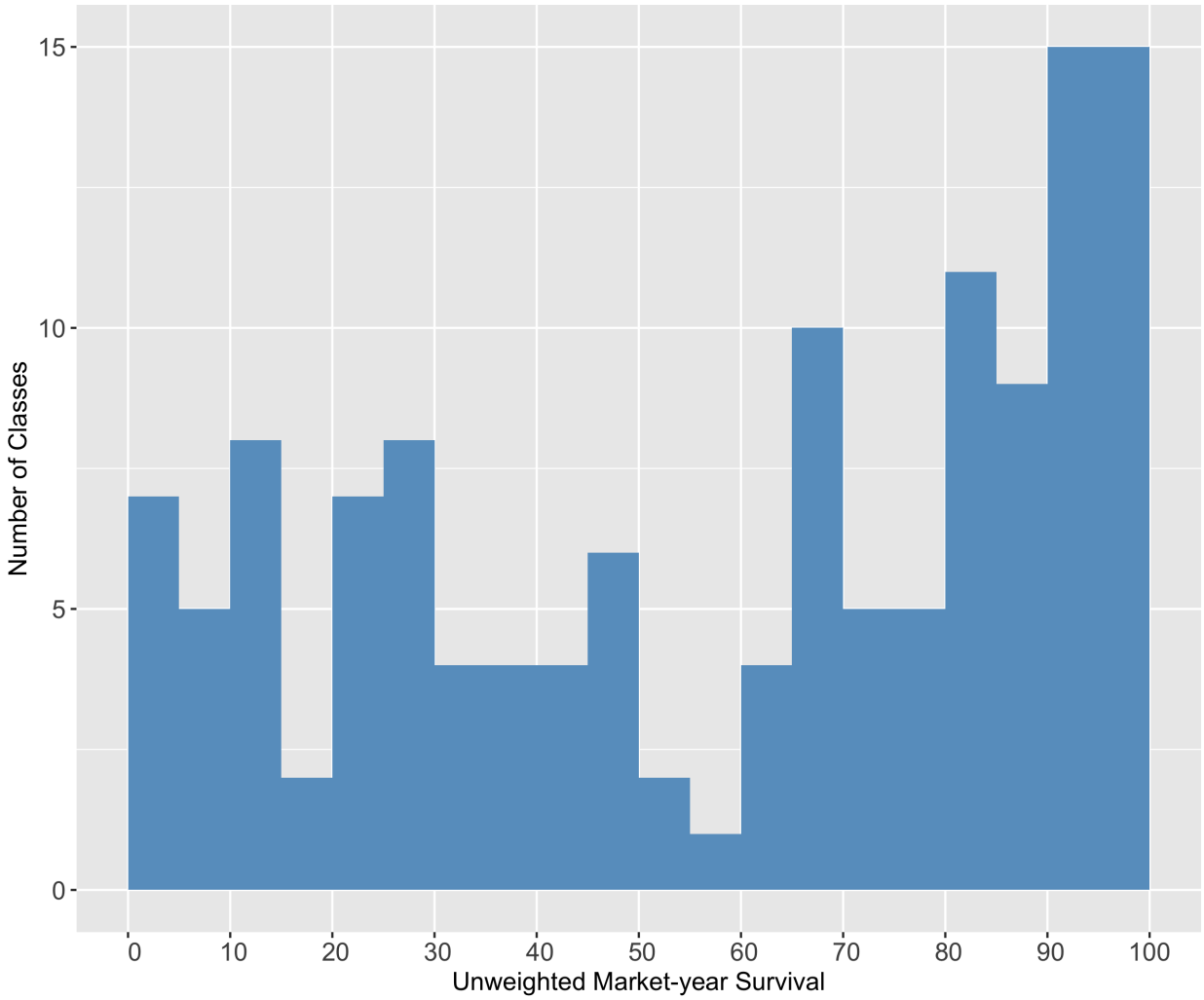
Notes: For each therapeutic class, we measure, out of the set of beneficiary-year pairs where the beneficiary took at least two drugs within the class in that year, what share of days supply in that class were accounted for by the focal (most-used) drug. This figure plots the distribution of that statistic across classes.

Appendix Figure A10: Focal Drug Days Supply Share for All Drug Users



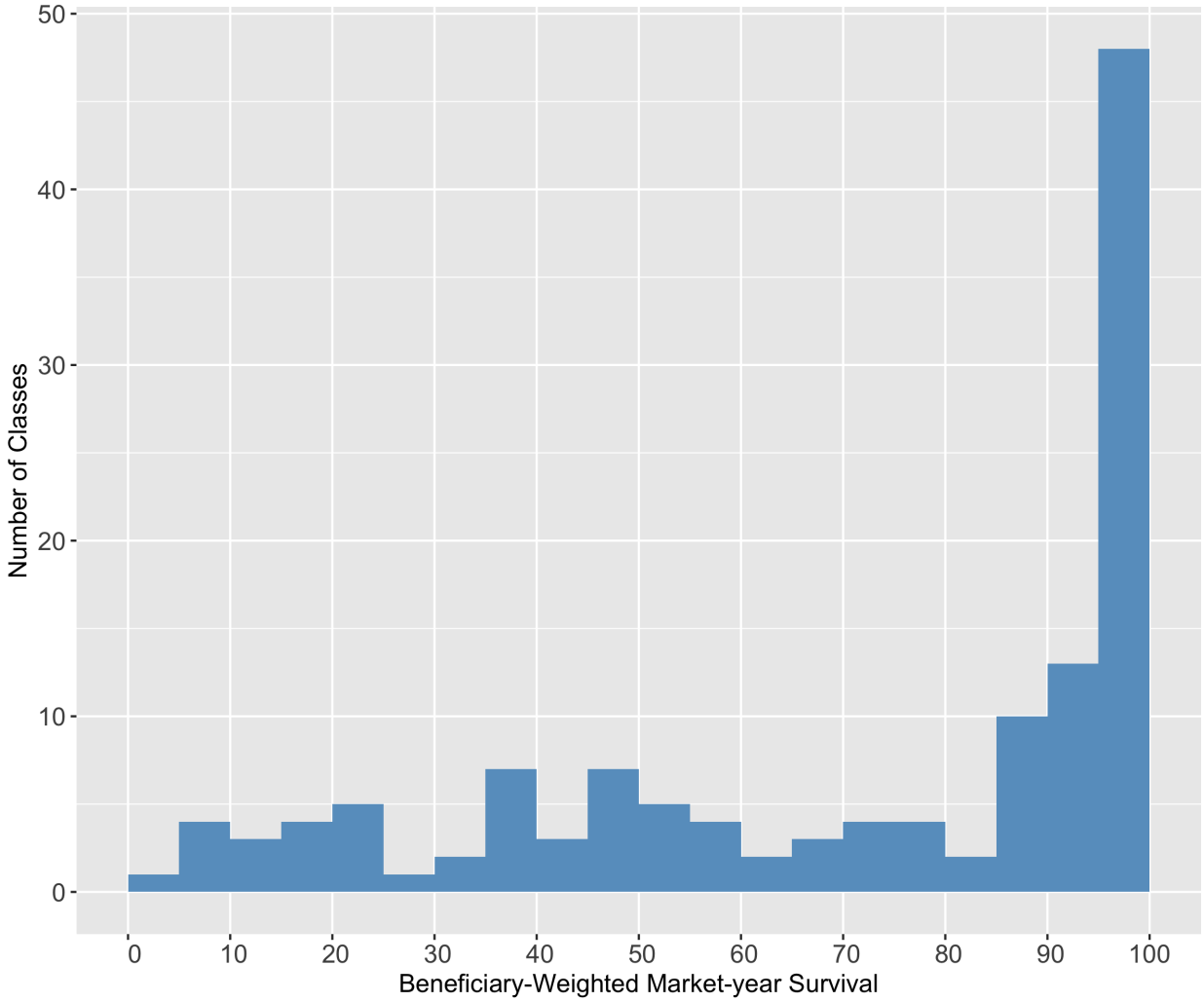
Notes: For each therapeutic class, we measure, out of the set of beneficiary-year pairs where the beneficiary took at least one drug within the class in that year, what share of days supply in that class were accounted for by the focal (most-used) drug. This figure plots the distribution of that statistic across classes.

Appendix Figure A11: Unweighted Market-Year Survival After Logit Restrictions



Notes: This figure plots the distribution, across classes, of the share of markets (region-year pairs) that have (1) at least one drug in the class that is under a prior authorization restriction in between 0 and 100% of plans; and (2) where at least two drugs in the class are filled.

Appendix Figure A12: Beneficiary-Weighted Market-Year Survival After Logit Restrictions



Notes: This figure plots the distribution, across classes, of the share of markets (region-year pairs) that have (1) at least one drug in the class that is under a prior authorization restriction in between 0 and 100% of plans; and (2) where at least two drugs in the class are filled. In this figure, markets are weighted by the number of beneficiaries represented in our sample.

E Revealed Preference Analysis: Additional Details

E.1 Deriving Consumer Surplus Loss

In Section 6.1, we use demand curves of the form $D(p) = D(0)e^{\frac{\epsilon}{100}p}$. In this Appendix, we briefly derive a closed-form expression for consumer surplus.

We note that consumer surplus over the range Θ is

$$CS = \int_{\Theta} V_d(q)dq = \int_{\Theta} D^{-1}(q)dq$$

with the second equality due to the fact that we have assumed that $V_d(\theta) = W_d(\theta)$, and $W_d(\theta) = D^{-1}(\theta)$.

Note that since $D(p) = D(0)e^{\frac{\epsilon}{100}p}$, then $D^{-1}(q) = \frac{100}{\epsilon}\log\left(\frac{q}{D(0)}\right)$. Given this, we can also note that

$$\int \frac{100}{\epsilon}\log\left(\frac{q}{D(0)}\right)dq = \frac{100}{\epsilon}\left[q\log\left(\frac{q}{D(0)}\right) - q\right]$$

In the section, we generally take integrals over regions of the form $[aD(0), bD(0)]$. For such a region, the integral is therefore

$$\begin{aligned}\int_{aD(0)}^{bD(0)} \frac{100}{\epsilon}\log\left(\frac{q}{D(0)}\right)dq &= \frac{100}{\epsilon}\left[q\log\left(\frac{q}{D(0)}\right) - q\right]_{aD(0)}^{bD(0)} \\ &= \frac{100D(0)}{\epsilon}\left[b\log(b) - a\log(a) - (b-a)\right]\end{aligned}$$

noting that, while this antiderivative is undefined at $q = 0$, $\lim_{q\to 0} q\log(q) - q = 0$. Note that this measure of consumer surplus is linear in $D(0)$, as well as being linear in the reciprocal of ϵ, the semi-elasticity of demand.

At the end of that section, we relax the assumption that willingness-to-pay is equal to value, and replace it with $W_d(\theta_{id}) = \rho V_d(\theta_{id})$ for $\rho \in (0, 1]$, which is equivalent to $\frac{W_d(\theta_{id})}{\rho} = V_d(\theta_{id})$. Consumer surplus is now

$$CS^{Debiased} = \int_{\Theta} V_d(q)dq = \int_{\Theta} \frac{W_d(q)}{\rho}dq = \frac{1}{\rho}\int_{\Theta} D^{-1}(q)dq = \frac{1}{\rho}CS$$

i.e., debiased consumer surplus is linear in the 'rational' consumer surplus measure. Note that if we want to find the ρ such that net welfare is zero, we need

$$\begin{aligned}NFS + \Delta CS^{Debiased} &= 0 \\ NFS + \frac{1}{\rho}\Delta CS &= 0 \\ \frac{-\Delta CS}{NFS} &= \rho\end{aligned}$$

Noting that ΔCS is negative so the term on the left will be positive.

E.2 Provider-Based Revealed Preference Approach

Here we detail an alternative approach to measuring revealed preference through provider actions. In this approach we assume that decisions about which prescription drug the patient will consume are made entirely by the provider.

Consider a provider deciding whether to prescribe restricted drug d to patient i. Assume providers care about their own costs, but also put altruistic weight on the patient's preferences, such that provider utility is

$$u_{id} = \rho v_{id} - a$$

where ρ is the weight the provider places on patient preferences and a is the administrative cost of fulfilling a prior authorization request, where applicable. The provider will prescribe drug d if $\rho \Delta v_{id} = \rho V_d(\theta_i) \geq a$, resulting in a demand curve $D(a)$ that depends on administrative costs, with $D(a) = \int 1\{W_d(\theta_i) \geq a\} d\theta$, with $W_d(\theta_i) = \rho V_d(\theta_i)$, the willingness-to-do-paperwork (an analogue to willingness-to-pay).

If, as in Section 6.1, $W_d(\theta_i)$ is drawn from a zero-inflated exponential distribution with scale parameter $\frac{\epsilon}{100}$ and a mass at zero of $1 - D(0)$, then, as in the prior section, this structure gives rise to a demand curve that depends on administrative costs, $D_d(a) = D(0)e^{\frac{\epsilon}{100}a}$ for ϵ, the semi-elasticity of drug demand with respect to administrative costs. Under this structure, the demand curve for drugs once again reveals patient valuations for the drug; although, in this case, it specifically reveals how physicians value patient value for the drug. To simplify, we begin by assuming that physicians are perfectly altruistic in that they weight their patient's preferences equal to their own, i.e., $\rho = 1$.

To estimate the administrative cost semi-elasticity, we simply use the demand response to prior authorization restrictions that we observe in Sections 3 and 4. In response to prior authorization, providers prescribe restricted drugs 28.9% less. Our baseline calibration of provider-facing cost is \$22. These two numbers imply that the administrative cost semi-elasticity of prescription is $\epsilon = \frac{28.9}{22.48} = 1.29$. By this calibration, providers are several times more elastic to administrative costs relative to patients' elasticity to out-of-pocket prices.

As established in the prior section, the implied consumer surplus loss is inversely proportional to the elasticity of demand. Therefore, the loss estimated from this approach will be smaller than the loss estimated from the beneficiary-centered approach. We once again compute consumer loss under two screening scenarios: the best-case and the random case. Under those three assumptions, the consumer surplus loss is \$2and \$9 respectively.

These measures assume $\rho = 1$; however, we have no guarantee that physicians act in the best interests of their patients per se. It might be that physicians weight their own costs to a relatively greater extent than the value for their patients. We do not have a specific estimate of ρ. Instead, we can once again find the values of ρ that would make prior authorization restrictions generate utilitarian welfare losses on net. ρ has a stronger economic interpretation in this case: When ρ is low, providers care little about their patients' welfare, and therefore policymakers should not enforce screening mechanisms that make them responsible for allocating drugs to patients. For the best-case and random case scenarios, the maximum ρ to make prior authorization inefficient is 0.02 and 0.11 respectively.