

ANALYSIS GROUP

Law & Economics Symposium

CURRENT
TOPICS
IN LIFE
SCIENCES

WEBINAR SERIES

Health Consequences of Patient Cost Sharing: A Discussion with Harvard Professor of Health Policy Amitabh Chandra

Moderator: Noam Kirson, Analysis Group

April 28, 2021

Webinar Guidelines

- **You are currently in** view-only mode and your line is muted
- To **“ask a question”** click on the Q&A feature to submit your question
- **If you are experience technical difficulties**, please submit your concern via chat and our technician will assist you
- The slides from today’s webinar will be posted to the Analysis Group website next week



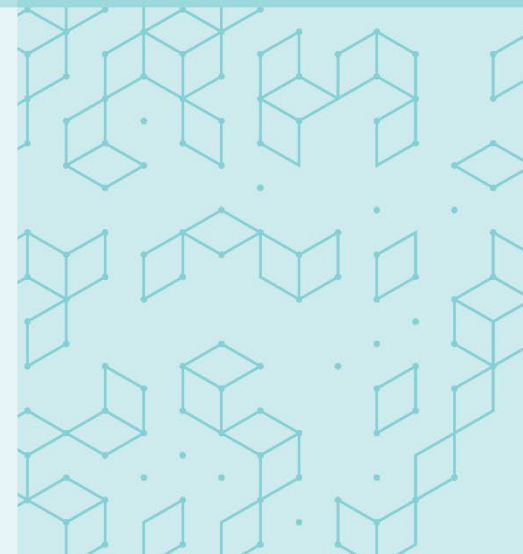
SAVE THE DATE

June 9, 2021

ANALYSIS GROUP

Law & Economics
Symposium

CURRENT
TOPICS
IN LIFE
SCIENCES



The Health Costs of Cost-Sharing

Amitabh Chandra PhD

McCance Family Professor of Business Administration, **Harvard Business School**

Ethel Wiener Zimmerman Professor of Public Policy, **Harvard Kennedy School of Government**

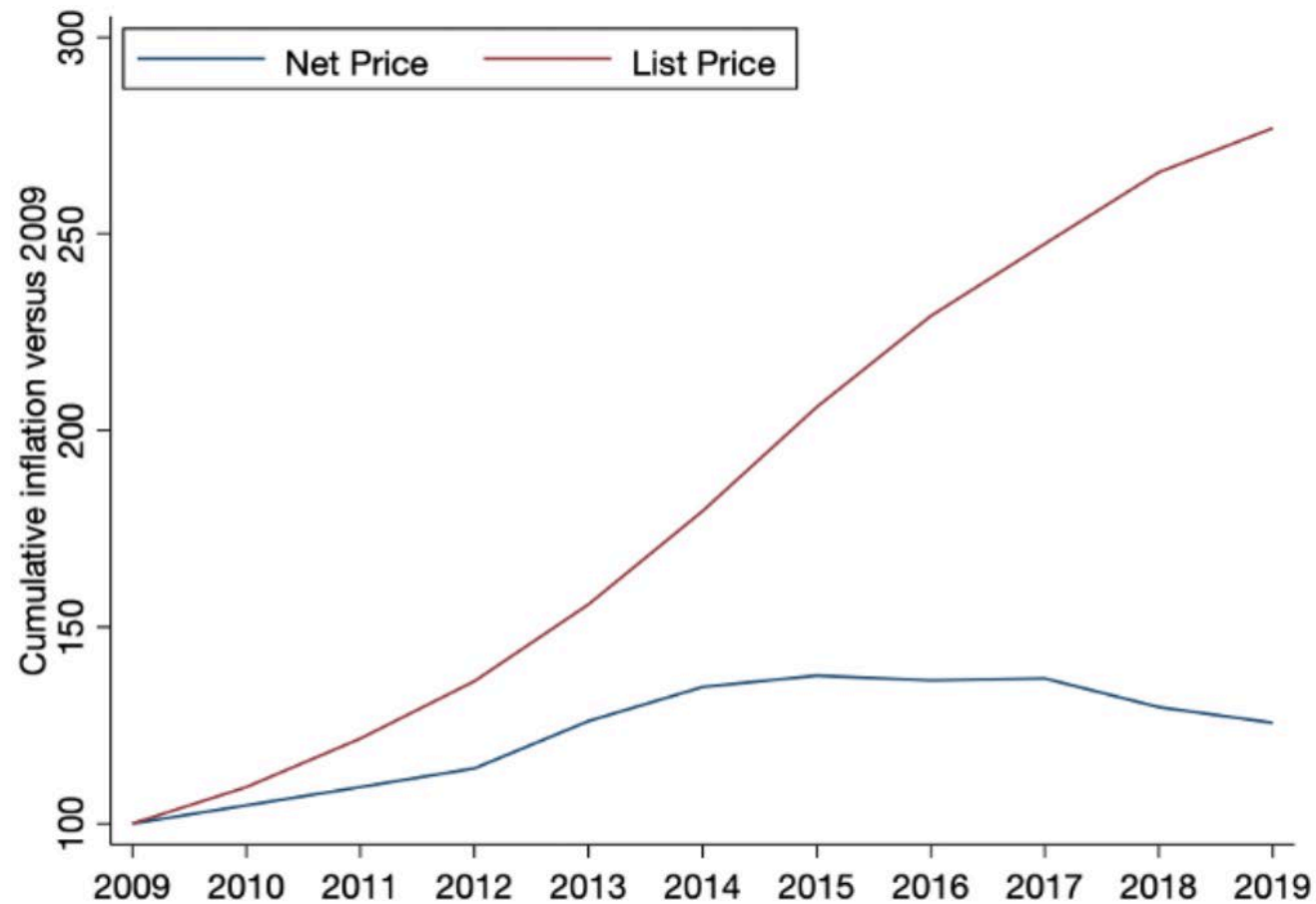


HARVARD | BUSINESS | SCHOOL



HARVARD Kennedy School

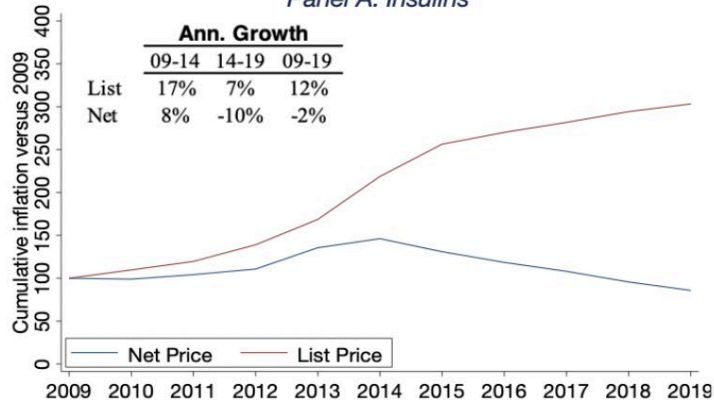
JOHN F. KENNEDY SCHOOL OF GOVERNMENT



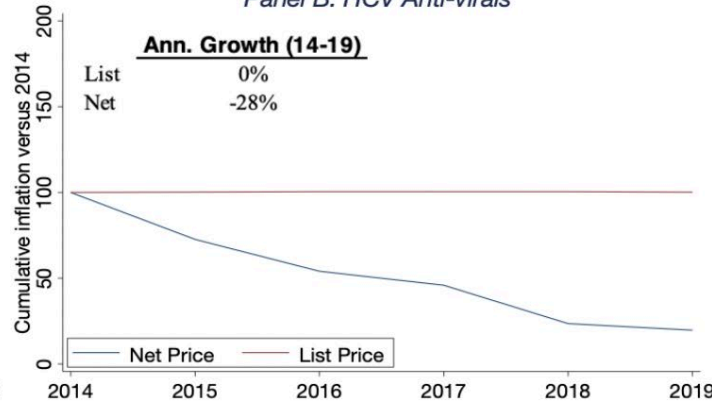
Year											Avg. annual inflation		
	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19	09-14	14-19	09-19
List Price	9%	11%	12%	14%	15%	15%	11%	8%	7%	4%	12%	9%	11%
Net Price	5%	4%	4%	11%	7%	2%	-1%	0%	-5%	-3%	6%	-1%	2%

Notes: Both panels reflect analysis of 1250 branded product-formulations sold in retail pharmacies for non-rare conditions, but the sample varies in each year due to entry and exit. Samples differ by year due to product entry and exit. See text for further details on exclusions. Panel B reflects list and net price inflation calculated using a Laspeyres Price Index for each year-pair. This reflects a chainweighted approach using the balanced sample of products in each pair of adjacent years. Annual inflation is compounded year over year to estimate cumulative inflation relative to 2009. Prices in 2009 are benchmarked at 100 percent.

Panel A: Insulins

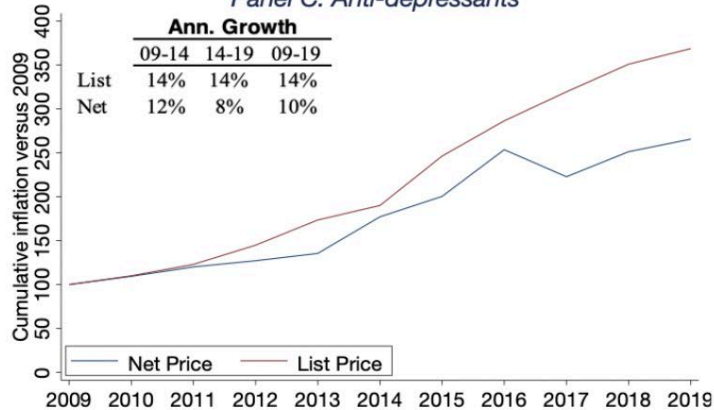


Panel B: HCV Anti-virals

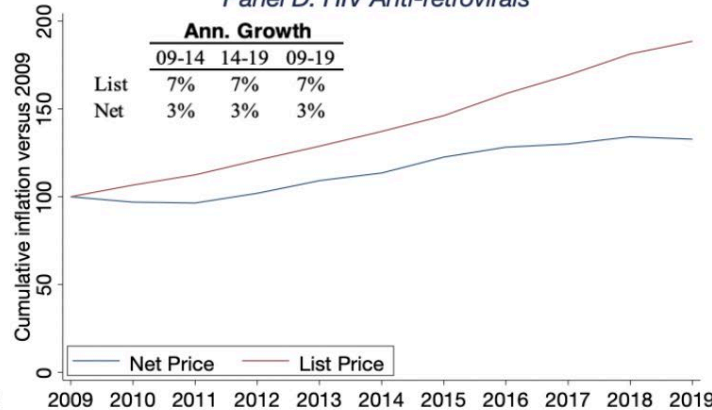


Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018	2019
Rebate	18%	26%	29%	35%	34%	46%	59%	64%	68%	72%	75%	6%	39%	52%	53%	63%	65%

Panel C: Anti-depressants



Panel D: HIV Anti-retrovirals



Year	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Rebate	18%	19%	20%	23%	30%	23%	33%	31%	42%	44%	45%	23%	30%	35%	35%	33%	34%	32%	33%	33%	34%	35%

Notes: Insulins included are in ATC-level 4 categories A10AB (fast-acting), A10AC (intermediate acting), A10AD (fast-acting with intermediate or long-acting), or A10AE (long acting) and includes 27 product-formulations: afrezza (2 formulations), apidra, basaglar, humalog / mix (8 formulations), humulin / mix (8 formulations), lantus (3 formulations), soliqua, toujeo (2 formulations), and xultophy. The HCV anti-virals category (ATC4 category J05AP) includes 14 product-formulations: daklinza (3 formulations), eplclusa, harvoni, mavvyret, olysio, sovaldi, victrelis, viekira / xr, vosevi, and zepatier. HCV products shown starting in 2014 due to launch of Sovaldi in late 2013. The anti-retroviral drugs are identified as the subset of ATC3 category J05A (direct acting anti-virals) that is approved for HIV and include 71 product formulations: atripla, biktarvy, combivir, complera, crixivan (3 formulations), descovy, emtriva (2 formulations), epivir (3 formulations), epivir hbv (3 formulations), epzicom, fuzeon, genvoya, intelence (2 formulations), isentress (5 formulations), juluca, kaletra (3 formulations), lexiva (2 formulations), norvir, odefsey, prezista (7 formulations), reyataz (6 formulations), selzentry, stribild, sustiva (4 formulations), symtuza, tivicaay (3 formulations), triumeq, trizivir, truvada (4 formulations), viread (5 formulations), and ziagen (2 formulations). The anti-depressants category (ATC3 category N06A) includes 58 product-formulations: apelenzin (3 formulations), celexa (3 formulations), cymbalta (3 formulations), fetzima (5 formulations), lexapro (4 formulations), pristiq (3 formulations), sarafem (3 formulations), savella (5 formulations), trintellix (3 formulations), viibryd (5 formulations), wellbutrin sr (5 formulations), wellbutrin xl (2 formulations), and zoloft (4 formulations).

- Patient cost-sharing, like deductibles and coinsurance, is tied to list prices
- What are we getting from this cost-sharing?
 - Are we reducing overuse?
 - Or are we increasing underuse?
- Spending on medicines is a poor proxy for social-welfare, or for overuse and underuse

The Health Costs of Cost-Sharing

Amitabh Chandra

Harvard Kennedy School, Harvard Business School, and NBER

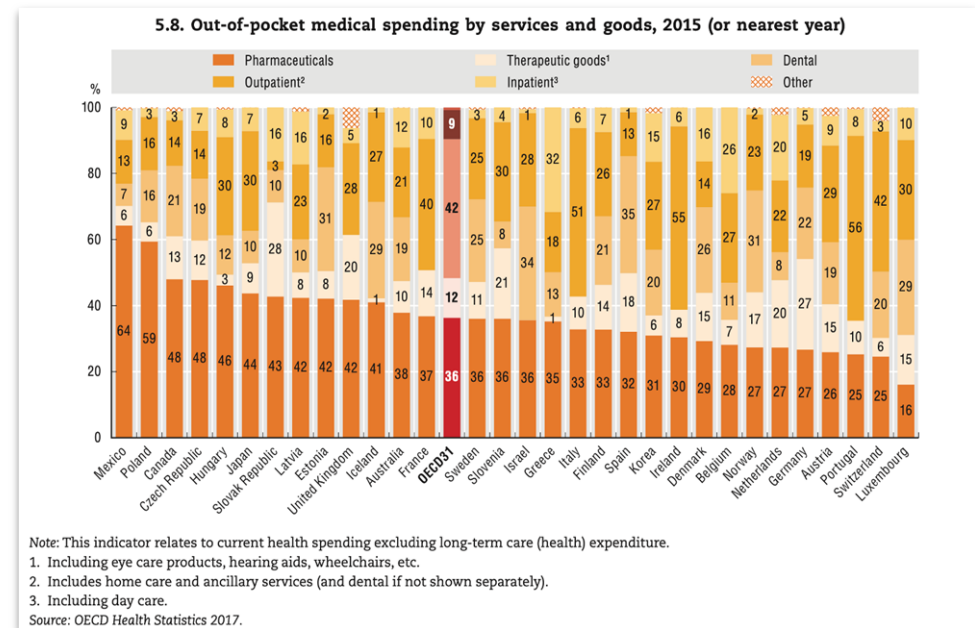
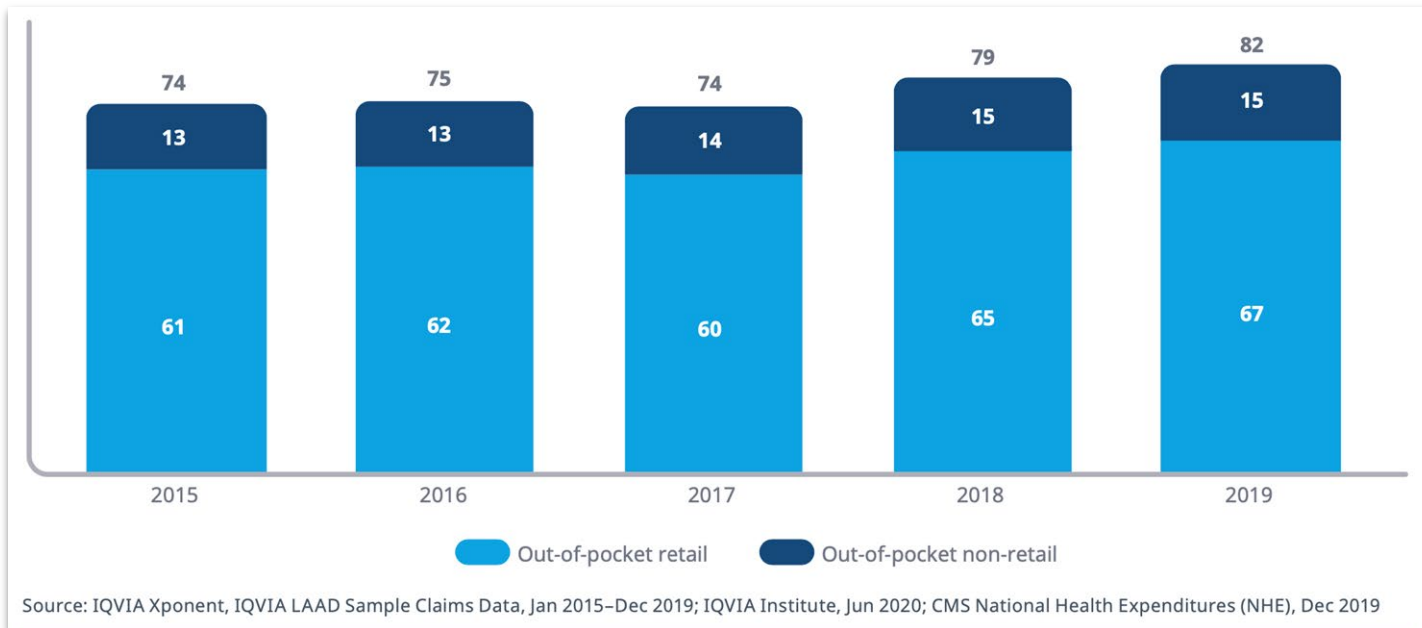
Also implicated:

Evan Flack (Harvard Kennedy School)

Ziad Obermeyer (UC Berkeley Public Health)



Patient Cost-Sharing on Medicines



Are there health effects from cost-sharing?

- Cost-sharing is everywhere, and growing
 - Efficient if care is overused (moral hazard)
- But cost-sharing could also harm health if patients misperceive benefits and cut back on valuable treatments (behavioral hazard)
 - Hard choice problem: patient on 5 Rx could rank them in 120 different ways
 - High dimensional choice problem: survival, side-effects, symptoms, price amplified by distal nature of outcomes and proximal nature of prices
- Growing literature on behavioral hazard
 - Hospital spending “offsets” from small copayments (Chandra et al., 2010 AER)
 - After heart attack, cutbacks on drugs for... heart attack (Choudhry et al., 2011 NEJM)
 - Indiscriminate cutbacks: high- and low-value care alike (Brot-Goldberg et al., 2017 QJE)
 - Raises possibility that there is harm

Detecting health costs of cost-sharing — 2 challenges

- Prices are not randomly assigned
 - Reflect past utilization; which reflects health and choices
 - Need randomization of prices (RAND, Oregon HIE)
- But most RCTs are totally under-powered to detect mortality
 - e.g., detecting 10% change in 1% mortality (age 65) requires $n=325,000$
 - Oregon HIE treatment group had $n=9,000$; RAND HIE was $n=5,500$
 - So we use the price-elasticity of demand, as a proxy for health
 - (...but interpret this elasticity through the lens of moral-hazard)
- But demand response is indirect evidence
 - Physicians say patients are dropping “high-value” care
 - Economists say patients are dropping “low-value” care
 - What matters is health, not demand response

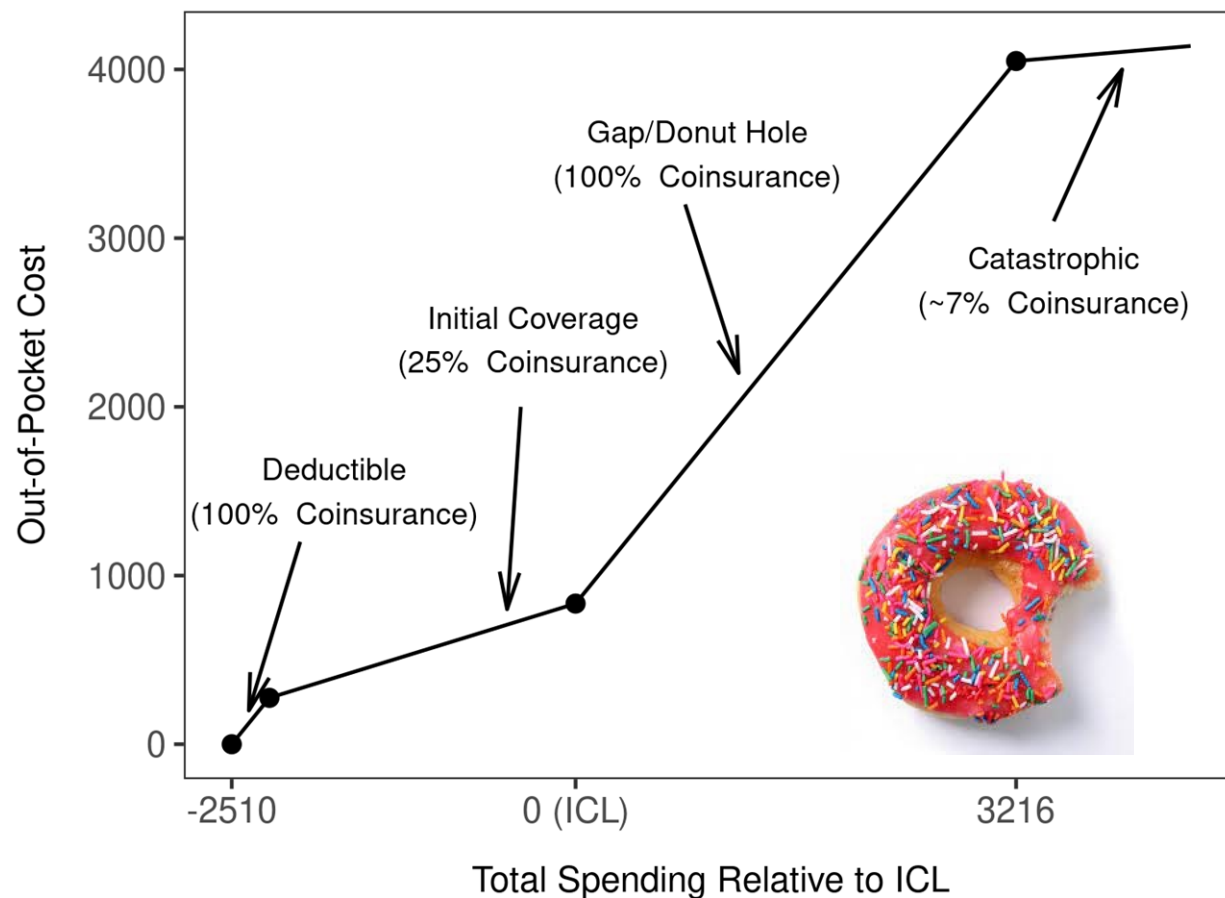
5 Facts on the health effects of cost-sharing for medicines

- Use design of Medicare Part-D to generate exogenous variation in end-of-year prices due to enrollment month
 - Deploy ML to boost power to detect mortality and sub-optimal decision making
 - Median price increase: 33.6% (11.0 p.p. on average, \$10.40/drug)
- Fact 1:
 - Causes 33% increase in mortality (~0.05 p.p./month)
 - Rational if 65 year olds had 1.5 years of life-expectancy; average is 20 years
 - Alternatively, implied life-year valuation at current life-expectancy: \$6,630/year
- Fact 2, 3, 4
 - Patients drop life-saving drugs (statins, blood pressure) with large mortality effects
 - Highest-risk patients cut back at least as much; often cut back more
 - Happens in rich and poor zip codes
- Fact 5
 - Patient face complex choices, respond with deadly heuristics
 - ~20% increase in patients who drop to zero drugs. Why?
- Bonus Fact
 - Literature on 'less medicines is more,' polypharmacy as more than 5 medicines, is picking up selection bias

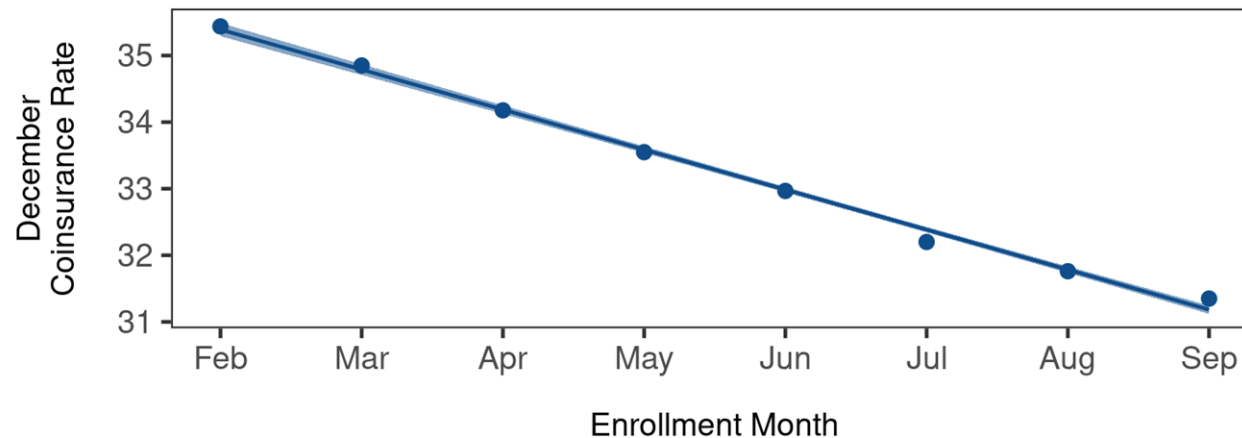
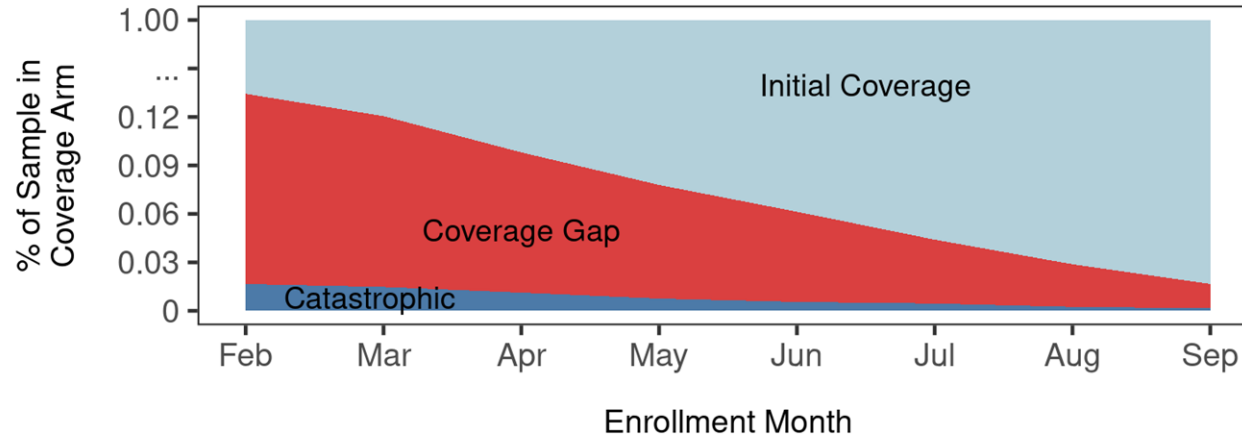
Want a setting with power, that is relevant for public-policy:
Medicare Part-D

OLS Intuition

$$Mortality_i^{EOY} = \beta_0 + \beta_1 Price_i^{EOY} + \epsilon_i$$



Earlier enrollees more likely to hit the coverage gap and catastrophic coverage, which generates December price differences by enrollment month

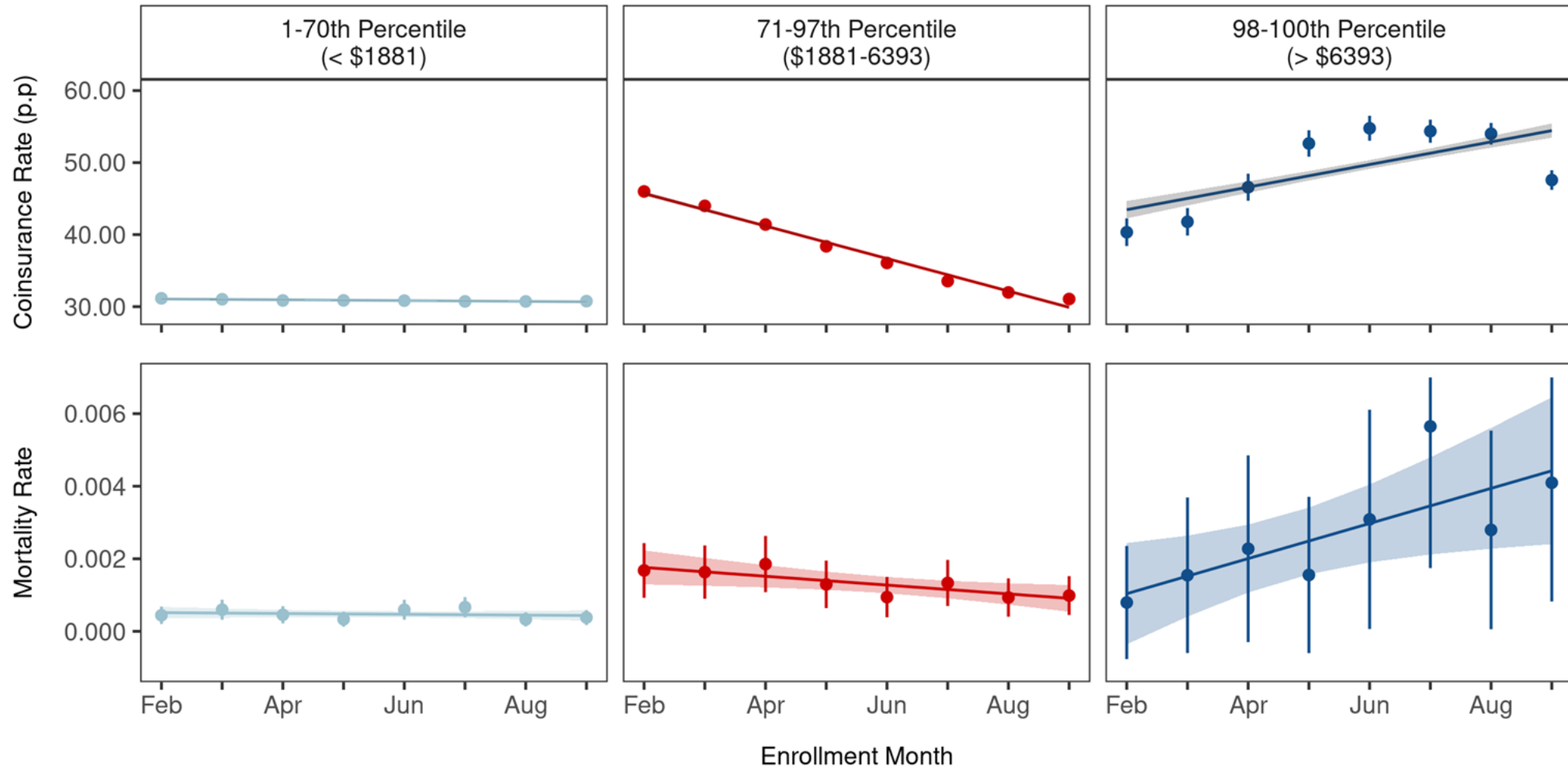


First Stage/ Reduced Form Intuition

$$Price_i^{EOY} = \pi_0 + \pi_1 EnrollmentMonth + u_i$$

$$Mortality_i^{EOY} = \theta_0 + \theta_1 EnrollmentMonth + \nu_i$$

All together



Machine learning lets us estimate individual-level risk

- Same setup as in spending prediction
 - Use first 3 months of data
 - Fit ML ensemble in duals, predict OOS in non-duals
- Use acute events/complications as outcome variable
 - **Cardiovascular:** heart attack/stroke
 - **Diabetes:** Diabetes Complications index (e.g. amputation, DKA)
 - **Respiratory:** respiratory failure, intubation, mechanical ventilation

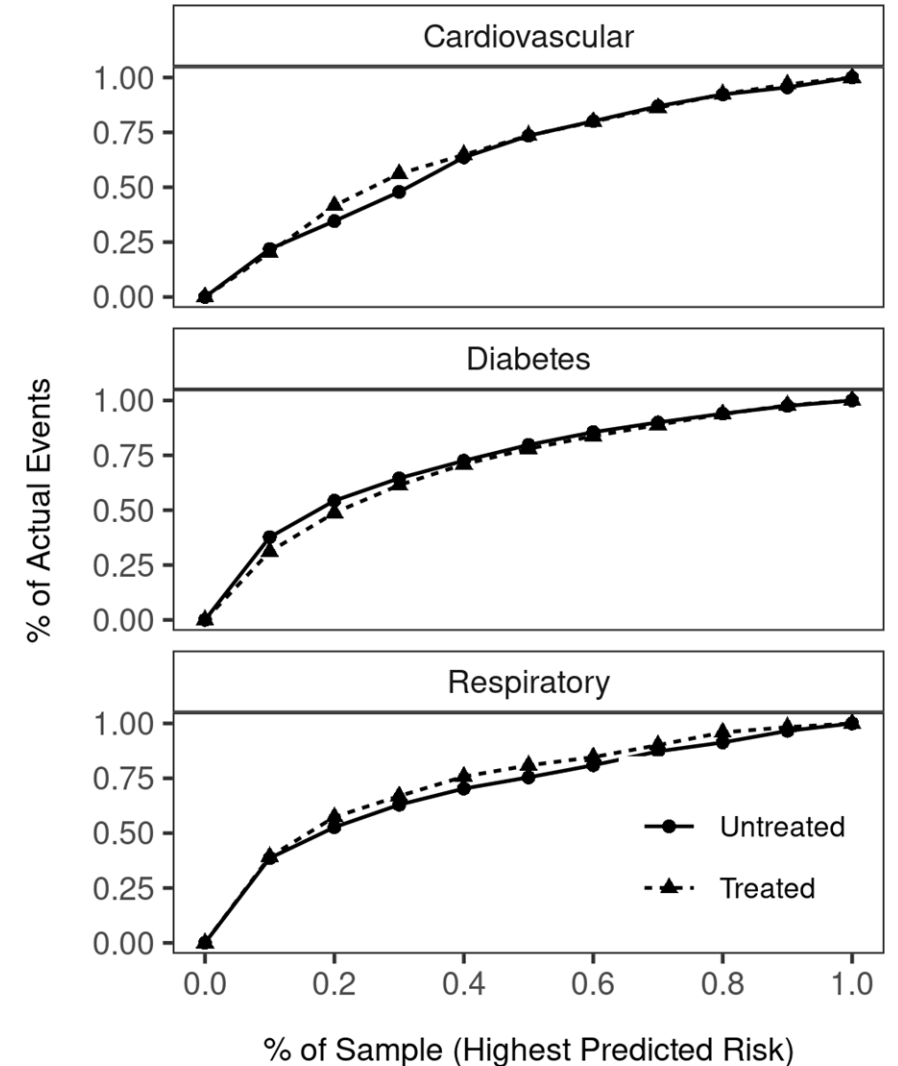


Table 7: Demand Response by Risk

	<i>2SLS: Number of Fills Estimate, by Group</i>		
	<u>Overall</u>	<u>By Risk</u>	<u>By Zip5 Income</u>
<i>Cardiovascular by risk/income:</i>			
Coinsurance rate	-0.00921*** (0.000588)	-0.00323*** (0.000714)	-0.00925*** (0.000747)
Coinsurance rate*Top 1/3	-	-0.00907*** (0.00105)	0.000298 (0.0012)
<i>Diabetes by risk/income:</i>			
Coinsurance rate	-0.00288*** (0.000306)	-0.00236*** (0.0005)	-0.00328*** (0.000402)
Coinsurance rate*Top 1/3	-	-0.00068 (0.00063)	0.00106* (0.000613)
<i>Respiratory by risk/income:</i>			
Coinsurance rate	-0.00226*** (0.000209)	-0.00207*** (0.000285)	-0.00239*** (0.000263)
Coinsurance rate*Top 1/3	-	-0.000337 (0.000418)	0.000343 (0.00043)

Wrapup

- 1 percent increase in coinsurance increases mortality by 3 percent. Does not look like ‘harvesting’
- Price-elasticity of demand is not sufficient for welfare
- Large effect– but would still not be detected in any study
- Not only is there a mortality effect, behavior doesn’t look rational
 - High risk patients drop their medicines
 - 20% increase in dropping to zero medicines
- Behavioral mechanisms—why do some patient drop all drugs?
 - Inattention? Memory? Giving up?
 - Information? Stay-tuned
- 3 Trillion \$ Question: How do we redesign insurance to account for behavioral biases?

