Screening in Contract Design: Evidence from the ACA Health Insurance Exchanges

Michael Geruso (UT Austin)
Timothy Layton (Harvard)
Daniel Prinz (Harvard)

November 2017
FTC Microeconomics Conference

Tension between consumer choice, nondiscrimination, and selection

- In Exchanges (and privatized Medicaid and Medicare), insurers must:
  1. Enroll anyone who wants to join a plan
  2. Not tie premiums to health status (think pre-existing conditions)

Tension between consumer choice, nondiscrimination, and selection

- In Exchanges (and privatized Medicaid and Medicare), insurers must:
  1. Enroll anyone who wants to join a plan
  2. Not tie premiums to health status (think pre-existing conditions)
- These regulations enforce “fairness” and provide protection against long-term risk (Handel, Hendel, Whinston, 2015)
- But open the door for inefficiencies related to selection
  - Health insurance contracts have many dimensions to cream-skim; price is just one screen

Tension between consumer choice, nondiscrimination, and selection

- In Exchanges (and privatized Medicaid and Medicare), insurers must:
    1. Enroll anyone who wants to join a plan
    2. Not tie premiums to health status (think pre-existing conditions)
- These regulations enforce "fairness" and provide protection against long-term risk (Handel, Hendel, Whinston, 2015)
- But open the door for inefficiencies related to selection
    - Health insurance contracts have many dimensions to cream-skim; price is just one screen
- Risk adjustment is widely used to address this cream skimming problem - Removes the financial incentive to avoid costly patients

Despite RA, Concerns about Screening in Exchanges

Thinking here about selection influencing not risk pool, but plan design

HIV Patients Accuse Health Plans of Using Drug Costs to Discriminate

by John Tozzi
jtozz
from BloombergBusinessweek

Health care law did not end discrimination against those with pre-existing conditions

By Kay Tillow

THE WALL STREET JOURNAL.

This copy is for your personal, non-commercial use only. To order presentation-ready copies for distribution to your colleagues, clients or customers visit http://www.djreprints.com.

http://blogs.wsj.com/pharmalot/2015/02/24/health-insurers-discriminate-against-patients-who-need-specialty-drugs/

LIFE

Health Insurers Discriminate Against Patients who Need Specialty Drugs?

By ED SILVERMAN
Feb 24, 2015 9:06 am ET

In a final rule issued last week concerning health benefits provided by the Affordable Care Act, the federal government noted that some health insurers are using "potentially discriminatory practices" against people with certain illnesses. As a result, they are paying more for their

ANDREW ROBERTS

Despite RA, Concerns about Screening in Exchanges

- Even in the absence of direct discrimination via premiums or coverage denials, possibility of dissuading consumers from joining plans via benefit design
- Anecdotes point to limiting access to entire classes of drugs as a backdoor discrimination. (Undoes intended protections for pre-existing conditions.)
- In November 2015, the National Multiple Sclerosis Society filed a comment with HHS's Office for Civil Rights explaining that "common health insurance practices that can discriminate against people with MS are formularies that place all covered therapies in specialty tiers."
- Separately, HHS has noted that one method indicating discrimination is to place "most or all drugs that treat a specific condition on the highest cost tiers."

Drug Tiering in Exchanges/Marketplaces

- We study selection-related formulary design in 2015 in the ACA Exchanges
- Investigate whether drugs treating chronic conditions are a plausible screen
  - Prices are relatively transparent
  - Patient needs are predictable, and coverage may be salient at enrollment

Drug Tiering in Exchanges/Marketplaces

- We study selection-related formulary design in 2015 in the ACA Exchanges
- Investigate whether drugs treating chronic conditions are a plausible screen
  - Prices are relatively transparent
  - Patient needs are predictable, and coverage may be salient at enrollment
- First, examine whether there is scope for selection: Does drug use predict profits net of risk adjustment? (Yes)

Drug Tiering in Exchanges/Marketplaces

- We study selection-related formulary design in 2015 in the ACA Exchanges
- Investigate whether drugs treating chronic conditions are a plausible screen
  - Prices are relatively transparent
  - Patient needs are predictable, and coverage may be salient at enrollment
- First, examine whether there is scope for selection: Does drug use predict profits net of risk adjustment? (Yes)
- Second, ask: Do formularies of Exchange plans track the incentive (Yes, with significant sophistication)

Adverse Selection and Contract Design in the Literature

- Lots of attention in the empirical literature to adverse selection in a fixed contracts setting (Einav, Finkelstein, and Cullen 2010)
  - Only contract prices respond to the enrollment pool
  - Doesn't connect to concerns about poor coverage for certain services
  - Also doesn't connect to the wide use of risk adjustment by regulators

Adverse Selection and Contract Design in the Literature

- Lots of attention in the empirical literature to adverse selection in a fixed contracts setting (Einav, Finkelstein, and Cullen 2010)
  - Only contract prices respond to the enrollment pool
  - Doesn't connect to concerns about poor coverage for certain services
  - Also doesn't connect to the wide use of risk adjustment by regulators
- Less empirical work on how the set of contracts offered in equilibrium is affected by selection patterns in a market
  - Despite lengthy and deep theoretical literature on the topic (Rothschild and Stiglitz 1976; Glazer and McGuire 2000; Veiga and Weyl 2016; Azevedo and Gottlieb 2017)
- Important to understand how contracts are used as screening devices
  - Important for evaluating the effectiveness of risk adjustment policies
  - We add here to findings in Medicare and pre-ACA individual markets by Carey (2017a,b), Decarolis and Guglielmo (2017), Lavetti and Simon (2016), Shepard (2016)

Part 1: How Well is Payment System Performing in Neutralizing Screening Incentives?

2 broad categories of regulations aimed to curb design for selection

1. Coverage mandates
   - EHB require Marketplace plans to cover at least one drug in each USP therapeutic category and class
   - No requirement about how drugs should be tiered within a class

2 broad categories of regulations aimed to curb design for selection

1. Coverage mandates
   - EHB require Marketplace plans to cover at least one drug in each USP therapeutic category and class
   - No requirement about how drugs should be tiered within a class
2. Payment adjustments: Intended to align profit maximizing contracts with socially efficient contracts
   - Risk adjustment
   - Reinsurance

Selection Incentive - Data

- Marketscan administrative health insurance claims data (mostly self-insured employers) for about 12M people
- For each individual we observe
  - Demographics
  - Total spending
  - Prescription drug claims
  - All diagnoses appearing in claims
- Use HHS formulas/software to simulate person-specific plan revenues
  - Premiums
  - Risk adjustment transfer
  - Reinsurance
- Note that this is not Exchange data: Instead, we use it to produce out-of-sample predictions of which drugs insurers are incentivized to ration due to selection

Selection Incentive - Simulating Revenue

- Patient-specific costs, C_i are the sum of all claims in the year
  For each i, sum *all* spending (not just drug costs, not just related costs)

- Patient-specific revenues, R_i, are:

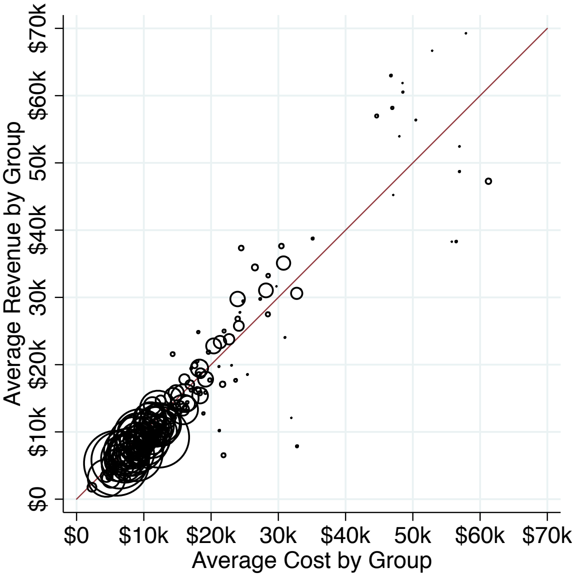
$$\underbrace{\text{actuarially fair premium}}_{\text{avg costs in sample}} + \underbrace{\text{implied RA}}_{f(\text{diagnoses, demographics})} + \underbrace{\text{implied reinsurance}}_{f(\text{realized costs})}$$

- This gives person-level profitability. Next aggregate up to means among groups who consume each drug.

Selection Incentive - Aggregating up to Therapeutic Classes

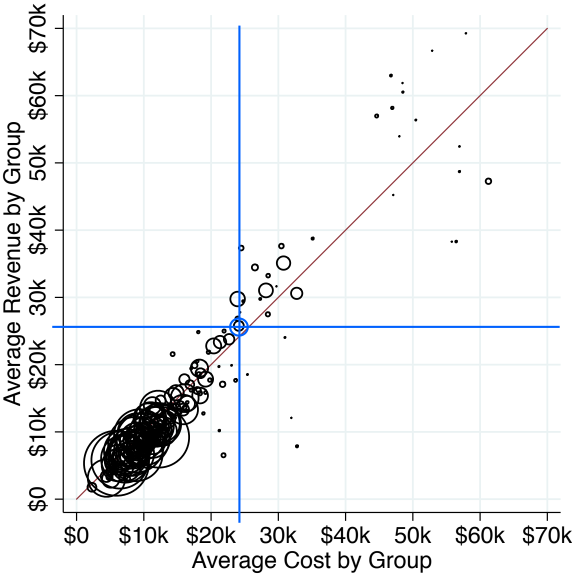
- We group into standard therapeutic classes using REDBOOK e.g., *Anticoagulants* (blood thinners), *Antihyperlipidemics* (statins); *Oral Contraceptives*; *Antidiabetic Agents, Insulins*
- 220 mutually exclusive drug classes c
- Goal is to avoid conflating screening with steering patients to lower cost alternatives among classes of substitutes.
- From patient-specific costs, C_i, and revenues, R_i, calculate means $\overline{C_c}$ and $\overline{R_c}$ among consumers who fill a prescription for a drug in class c

Fact 1: For most classes, selection incentives neutralized



zoom in zoom out

Fact 1: For most classes, selection incentives neutralized



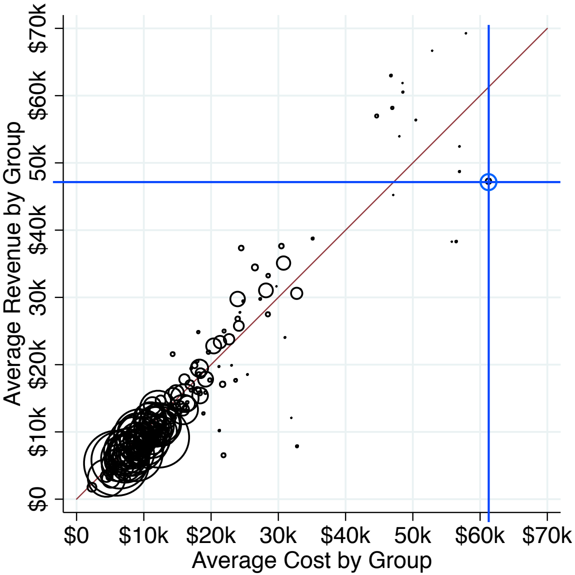
vasodilating agents
(treat angina)

~$24,000 in costs

~$26,000 in revenue =

$4,200 in premiums,
$17,878 in RA, and
$3,680 in reinsurance

Fact 2: For some outliers, drug consumption signal of profitability



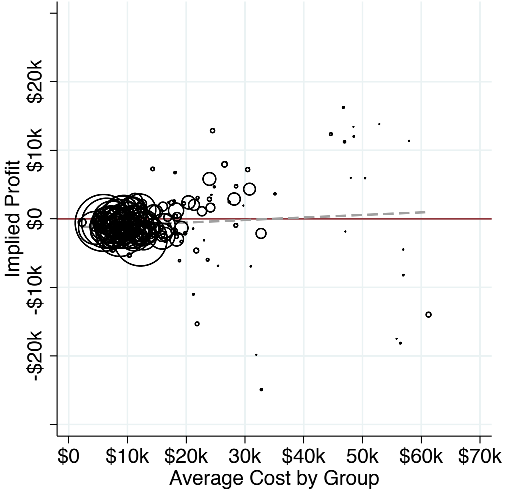
biological response modifiers (treat multiple sclerosis, others)

~$61,000 in costs

~$47,000 in revenue =

$4,200 in premiums, $34,420 in RA, and $8,648 in reinsurance

Fact 3: No overall correlation between profitability and cost



- No correlation btwn cost and implied profit
- Implies RA + Reinsurance succeed in decoupling profitability from patient costs on avg
- Implies that if plan designs track these incentives, some sophistication on part of insurers

zoom in zoom out

Selection Incentives - Top Drug Classes

Here limiting to classes with $> 0.01\%$ takeup

Class	Most Used Drug in Class	Conditions Treated by Most Used Drug	Net Loss: Cost - Revenue
(1)	(2)	(3)	(4)
Largest Incentives to Avoid			
Gonadotropins, NEC	Ovidrel	infertility in women	$15,326
Biological Response Modifiers	Copaxone	relapsing multiple sclerosis	$13,977
Opiate Antagonists, NEC	naltrexone	substance abuse disorders	$5,977
Ovulation Stimulants, NEC	clomiphene citrate	infertility in women	$5,304
Pituitary Hormones, NEC	desmopressin	diabetes insip., hemophilia A	$4,633
Vitamin A and Derivatives, NEC	Claravis	severe nodular acne	$4,428
Analg/Antipyr, Opiate Agonists	hydrocodone-acetamin.	moderate to severe pain	$3,001
CNS Agents, Misc.	Lyrica	nerve pain; fibromyalgia; seizure	$2,965
Mydriatics EENT, NEC	atropine	poisonings; pre-surgical preparations	$2,877
Androgens and Comb, NEC	AndroGel	low testosterone	$2,688

Selection Incentives - Top Drug Classes

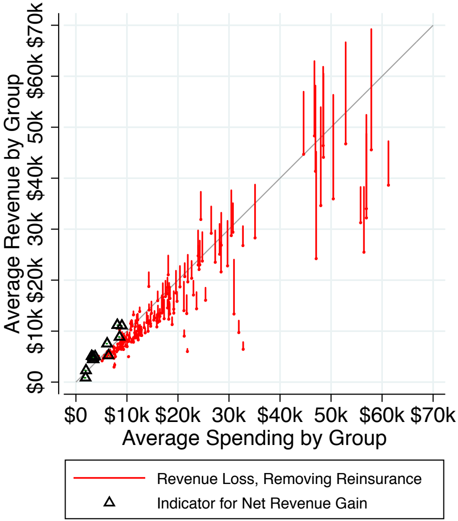
Largest Incentives to Attract

Antineoplastic Agents, NEC	methotrexate sodium	various cancers; various autoimmune diseases	-$2,885
Multivit Prep, Multivit Plain	Folbic	vitamin deficiency	-$3,058
Coag/Anticoag, Anticoagulants	warfarin	blood clots; stroke prevention	-$4,328
Cholelitholytic Agents, NEC	ursodiol	primary biliary cirrhosis; gallstones	-$4,751
Diuretics, Loop Diuretics	furosemide	edema due to heart, liver, kidney disease; high blood pressure	-$5,813
Ammonia Detoxicants, NEC	lactulose	complications of liver disease	-$7,181
Anticonv, Hydantoin Derivative	phenytoin sodium ext.	seziures; heart arrhythmias; neuropathic pain	-$7,275
Cardiac, Antiarrhythmic Agents	amiodarone	heart arrhythmias	-$7,942
Digestants and Comb, NEC	Creon	chronic pancreatitis; cystic fibrosis; pancreatic cancer	-$12,350
Cardiac, Cardiac Glycosides	Digox	heart arrhythmias; heart failure	-$12,857

Why the 'Errors' in the Payment System?

- Possible technological change in the intervening period between calibration and now (Carey 2016)
- HHS-HCC system based on Medicare Advantage's CMS-HCC system; in fact, does a good job compensating diabetes and heart disease.
- More generally, no reason to believe that predictors (drug utilization) that were not included in the RA algorithm are orthogonal to profitability

Fact 4: Reinsurance affects predictable profitability



- For the low cost groups (triangles on left) there is a small increase in profitability
- For the high cost groups (red lines on right) there is a large decrease in profitability

Part 2: Does Formulary Design Track the Incentive?

Data

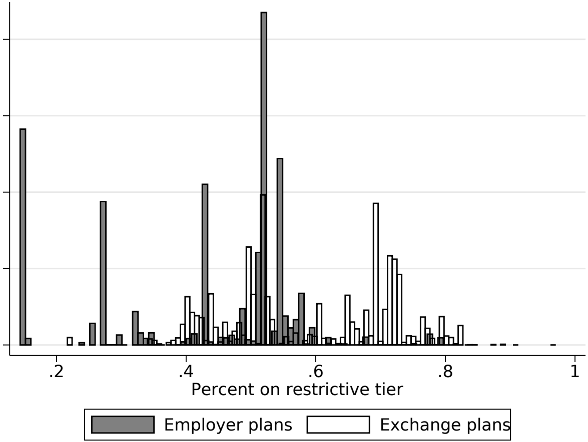
- Question: Are drugs that predict unprofitable patients covered ungenerously?
  - If an unprofitable group of consumers uses a cheap drug, an insurer will want to inefficiently distort coverage to be poor for that cheap drug
- Unit of analysis: drug class $\times$ plan, because class captures the set of substitutable therapies.
- We require data on formulary restrictiveness by drug class
  - Formulary tiering for the universe of state and federal exchanges in 2015 from MMIT

Restrictiveness - Measure

- To measure restrictiveness we use harmonized tiers
  1. Generic Preferred
  2. Generic
  3. Preferred
  4. Covered/ Non-preferred Brand
  5. **Specialty**
  6. **Not listed**
  7. **Medical**
  8. **Prior authorization/Step therapy**
  9. **Not covered**
- We draw a line below "covered" and call tiers below the line "restrictive" and tiers above the line "non-restrictive"
- For each REDBOOK drug class, we define formulary restrictiveness as the % of drugs in the class on a restrictive tier

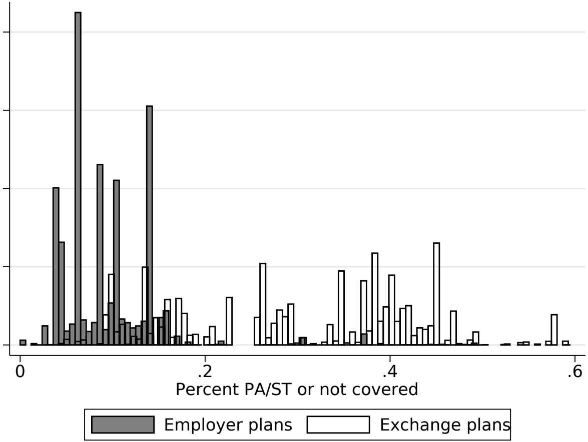
Fact 5: HIX Formularies More Restrictive on Price and Non-Price

Figure : Frequency of Assignment to Restrictive Tier

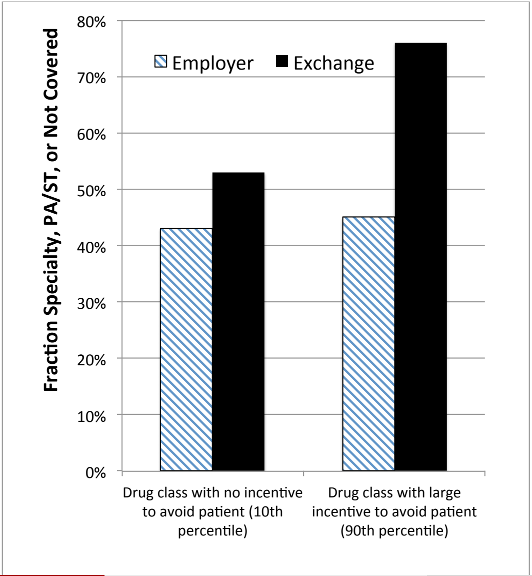


Fact 5: HIX Formularies More Restrictive on Price and Non-Price

Figure : Frequency of Non-price Hurdles to Access

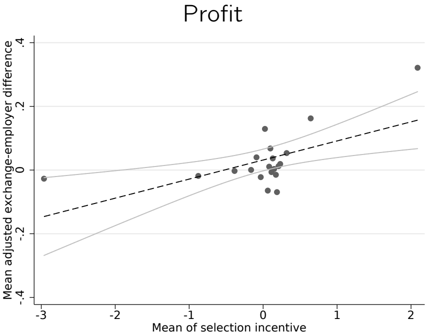


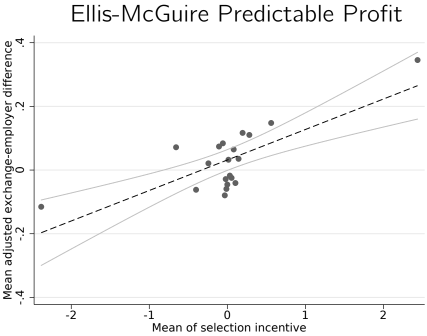
Fact 5: Drug Predicting Unprofitable Patients Are Restricted



Semiparametric Results

Grouping classes into 20 ventile bins by unprofitability.





Main result: Selection incentive predicts restrictive tiering

$$Y_{jc} = \beta[\text{HIX}_j \times S_c] + \gamma_c + \alpha_j + \epsilon_{cj}$$

	Panel A		
Dependent Variable:	Fraction of Class Tiered Specialty or Higher		
Selection Incentive Variable:	Ratio (Cost/Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(1)	(2)	(3)
Exchange X Selection incentive	0.046***	0.044**	0.046***
	(0.014)	(0.017)	(0.018)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440

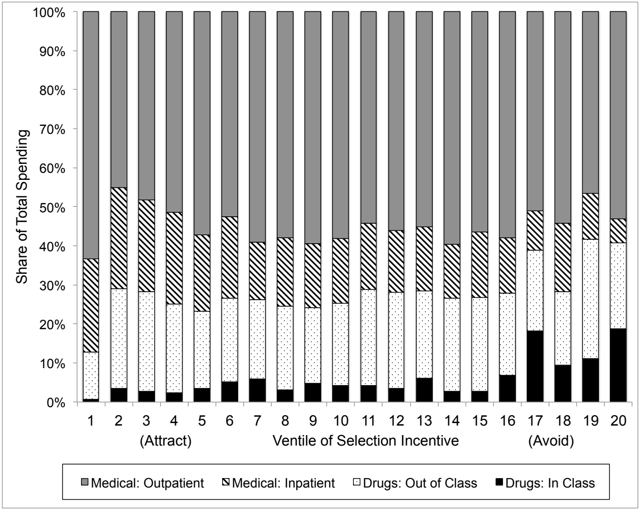
- Regressor of interest normalized into standard deviation
- 1 std dev increase in selection incentive corresponds to 4.5 pct pt increase in drugs in restrictive tiers

Main Results: Summary

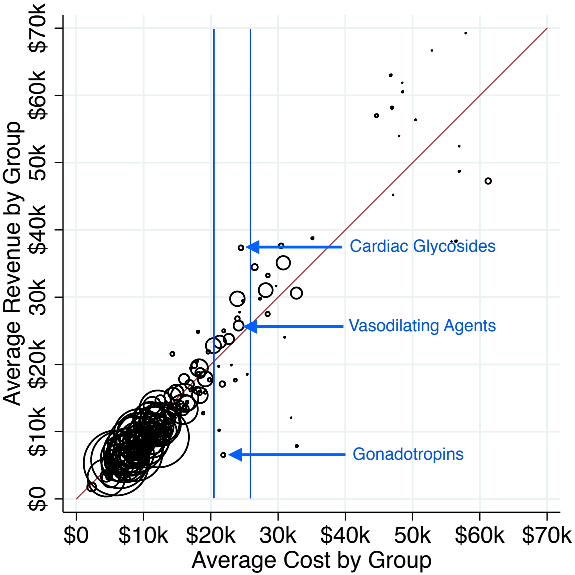
- Both cost-sharing and utilization management are apparent margins of distortion
  - Non-cost sharing hurdles to drug access matter too ▸ Other Hurdles
  - Utilization management may plausibly be a response to CSR
  - CSR reduces insurers ability to steer patients (efficiently) and to screen via copays/coinsurance (inefficiently)
- Alternative parameterizations tell same story
  ▸ Non-linear Results Tables ▸ Non-linear Results Plots
- Even after controlling for a linear relationship between S_c and restrictiveness:
  - Drugs in the top ventile bin face an additional 69 percent probability of being placed on a restrictive tier, compared to employer plans
  - Implies potential difference of thousands of dollars in OOP costs e.g. Capaxone costs $4,000, so 25% coinsurance is order of magnitude larger than $100 copay
  - These same eleven classes face 1.8X probability of being dropped from

Insurer Sophistication

Fact 6: Drugs are a small share of spending even among groups whose drug use flags them as unprofitable. Indicates sophistication.



What Are Insurers Responding To? Not Costs.



Already controlling for drug class FEs, but perhaps HIX plans are *differentially* attentive to high cost consumers...

Look within vertical slices: Equally costly but differentially profitable

Indicates sophistication

What Are Insurers Responding To? Net Profitability

Already controlling for drug class FEs, but perhaps HIX plans are *differentially* attentive to high cost consumers...

What Are Insurers Responding To? Net Profitability

Already controlling for drug class FEs, but perhaps HIX plans are *differentially* attentive to high cost consumers...

	Panel A					
	Implied Profits and Total Costs Horserace					
Selection Incentive Variable:	Ratio	Diff.	Ellis-McGuire	Ratio	Diff.	Ellis-McGuire
	(1)	(2)	(3)	(4)	(5)	(6)
Exchange X Selection incentive	0.051***	0.049***	0.041***	0.062***	0.064***	0.051***
	(0.015)	(0.016)	(0.013)	(0.017)	(0.018)	(0.016)
Exchange X Average total cost associated with class	0.042***	0.042***	0.041***			
	(0.011)	(0.014)	(0.009)			
Exchange X [Indicators for 20 total cost bins]				X	X	X
Therapeutic class FEs	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440

- $Y_{jc} = \beta[S_c \times \text{HIX}_j] + \delta[\text{Cost}_c \times \text{HIX}_j] + \gamma_c + \alpha_j + \epsilon_{cj}$

What Are Insurers Responding To? Net Profitability

Everything in a horserace...

	Panel C Profits, Drug Costs, and Total Costs Simultaneously					
	Ratio	Diff.	Ellis-McGuire	Ratio	Diff.	Ellis-McGuire
	(13)	(14)	(15)	(16)	(17)	(18)
Exchange X Selection incentive	0.045***	0.049**	0.049**	0.052***	0.027	0.024**
	(0.014)	(0.021)	(0.024)	(0.012)	(0.019)	(0.011)
Exchange X Average total cost associated with class	0.007	0.042*	0.039			
	(0.013)	(0.024)	(0.029)			
Exchange X Average drug-only cost associated with class	0.046**	0.001	-0.003			
	(0.018)	(0.029)	(0.037)			
Exchange X [Indicators for 20 total cost bins]				X	X	X
Exchange X [Indicators for 20 drug cost bins]				X	X	X
Therapeutic class FEs	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440

Ruling Out Other Explanations

Alternative Hypotheses

Recall that all regressions include drug class FEs, so any alternative hypothesis needs to generate *differential* incentives for HIX and ESI plans

1. Just incentivizing substitution to cheaper drugs? No.
2. Just about nudging toward generics? No.
   - A generic that predicts an expensive patient will face step therapy, utilization review, or exclusion from formulary
3. Incentivizing substitution to drugs with lower negotiated prices?
   - Include interaction between HIX and PBM-by-state fixed effects (compare Optum Rx Marketplace plans in Texas to Optum Rx ESI plans in Texas): Results unchanged
4. Moral hazard? No
   - No correlation between selection incentive measures and elasticity estimates from Einav, Finkelstein, Polyakova (2016) Elasticities vs Selection Incentive
   - Include interaction between HIX and elasticity estimates: Results unchanged

Just incentivizing substitution to cheaper drugs? No.

	Panel B					
Within-Class Subsample:	Least Expensive Drugs in Class					
	25th Percentile of Cost or Lower			10th Percentile of Cost or Lower		
Selection Incentive Variable:	Ratio	Diff.	Ellis-McGuire	Ratio	Diff.	Ellis-McGuire
	(7)	(8)	(9)	(10)	(11)	(12)
Exchange X Selection incentive	0.058***	0.049***	0.051**	0.061***	0.047**	0.048**
	(0.015)	(0.019)	(0.020)	(0.015)	(0.019)	(0.020)
Therapeutic class FEs	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440

- Here dependent variable includes only cheapest drugs within class
- This is not about efficiently steering consumers to low cost substitutes

Just about nudging toward generics? No.

	Panel B		
Within-Class Subsample:	Generic Drugs Only		
Selection Incentive Variable:	Ratio (Cost /Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(4)	(5)	(6)
Exchange X Selection incentive	0.040***	0.029*	0.024
	(0.013)	(0.015)	(0.019)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	192	192	192
Observations (plan X state X class)	749,184	749,184	749,184

- Here dependent variable includes only the generic drugs within each class
- A few classes dropped because no generics
- This is not about efficiently steering consumers to generic substitutes

Just Different PBMs with Different Upstream Prices? No. ▸ Back

Selection Incentive Variable:	Ratio	E-M	Ratio	E-M
	(1)	(2)	(3)	(4)
Marketplace X selection incentive	.041***	.038**	.046***	.042**
	(.013)	(.015)	(.014)	(.017)
Therapeutic class FEs	X	X	X	X
Plan FEs	X	X	X	X
PBM FE X selection incentive	X	X		
PBM FE X state X selection incentive			X	X
Therapeutic Classes	220	220	220	220
Observations (plan X state X class)	838,034	838,034	749,280	749,280

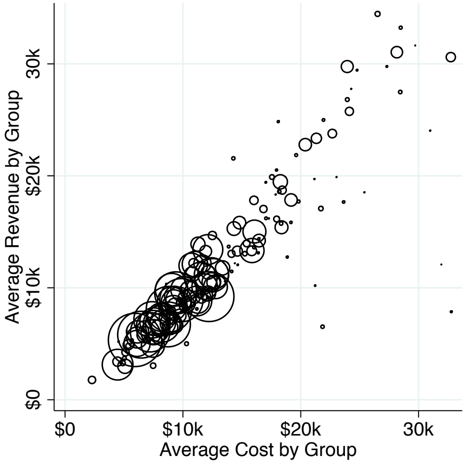
- e.g., Optum Rx Marketplace plans in Texas to Optum Rx ESI plans in Texas in cols 3 and 4
  $Y_{jc} = \beta[S_c \times \text{HIX}_j] + \sum \delta_k[S_c \times \text{PBM}_k] + \gamma_c + \alpha_j + \epsilon_{cj}$

Concluding Observations

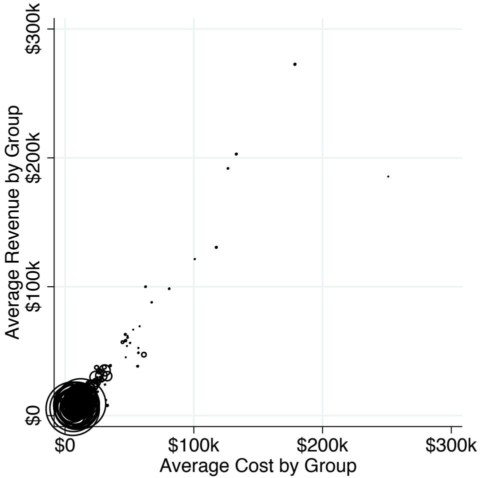
1. Risk adjustment + reinsurance do a good job overall in neutralizing screening incentives. *But some very unprofitable outliers exist*
2. Reinsurance important in reducing the incentive to avoid high-cost types
3. This is not about plans nudging consumers to lower cost or generic options
4. Both cost-sharing and utilization management are margins of distortion
5. It is not high drug costs that determine high cost sharing. It is drugs that are unprofitable, net of RA/Reinsurance. We see plans making it hard/expensive to access even cheap drugs.
6. EHB cannot solve this problem. Too many hard to measure and hard to regulate plan features (prior-authorization, requirement to use in-house mail-in pharmacy)
7. Problems may be solveable with fairly minor reforms
    - Incorporating diagnoses X drug utilization into RA scheme; currently considered

APPENDIX

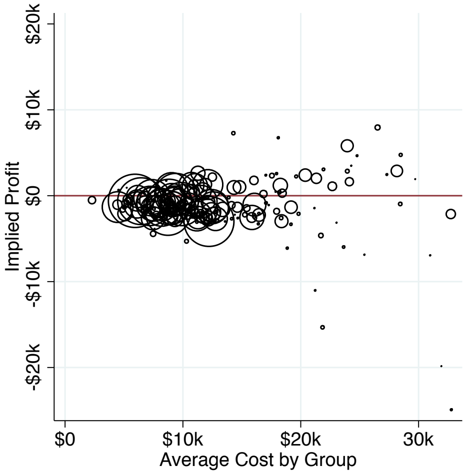
Fact 1: For most classes, selection incentives neutralized ▸ Back



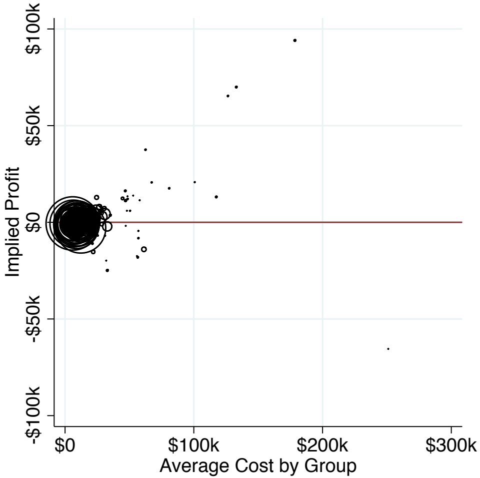
Fact 1: For most classes, selection incentives neutralized ▸ Back



Fact 3: No overall correlation between profitability and cost ▸ Back

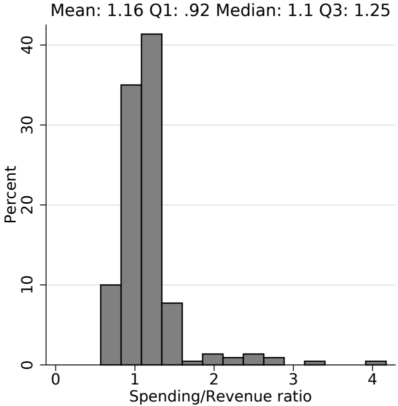


Fact 3: No overall correlation between profitability and cost ▸ Back

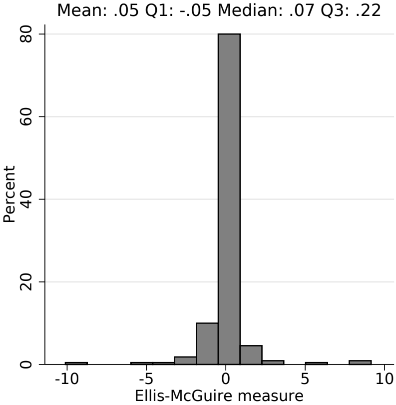


Most classes are clustered very near neutral

Ratio Measure



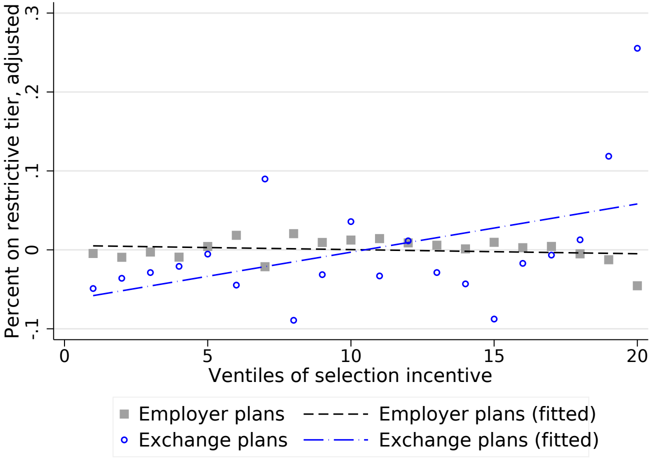
Ellis-McGuire Measure



Residuals: Difference Measure

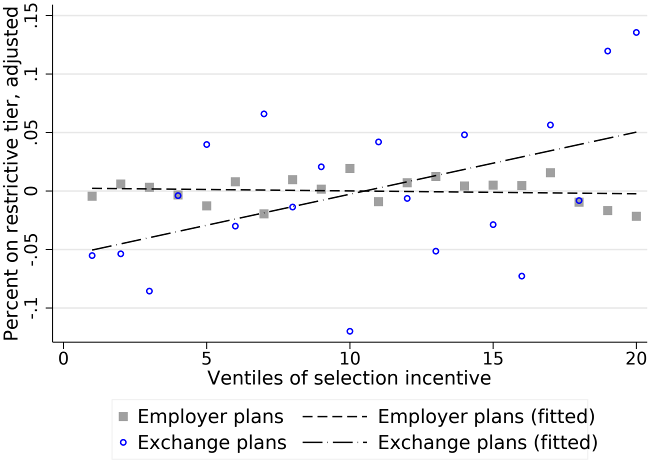
Residuals from $Y_{jc} = \gamma_c + \alpha_j + \epsilon_{cj}$

Grouping classes into 20 bins by selection incentive (Difference). ▸ back



Residuals: Ratio Measure

Residuals from $Y_{jc} = \gamma_c + \alpha_j + \epsilon_{cj}$
Grouping classes into 20 bins by selection incentive (Ratio). ▸ back



Non-cost sharing hurdles to drug access matter too

$$Y_{jc} = \beta[S_{mc} \times \text{HIX}_j] + \gamma_c + \alpha_j + \epsilon_{cj}$$

back

	Panel B		
Dependent Variable:	Fraction of Class Prior Auth./Step Therapy/Not Covered		
Selection Incentive Variable:	Ratio (Cost/Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(7)	(9)	(11)
Exchange X Selection incentive	0.018*	0.020*	0.018*
	(0.011)	(0.011)	(0.010)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440

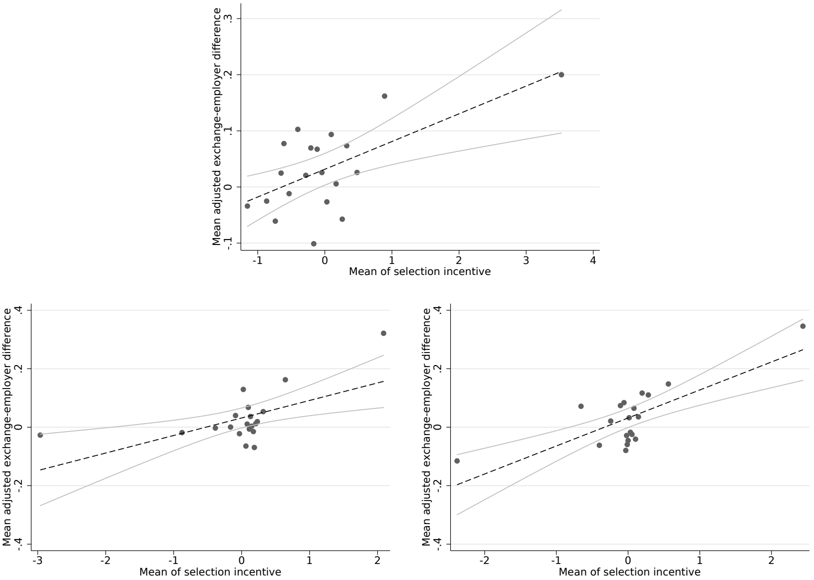
Main Result: Non-linear Version

Back

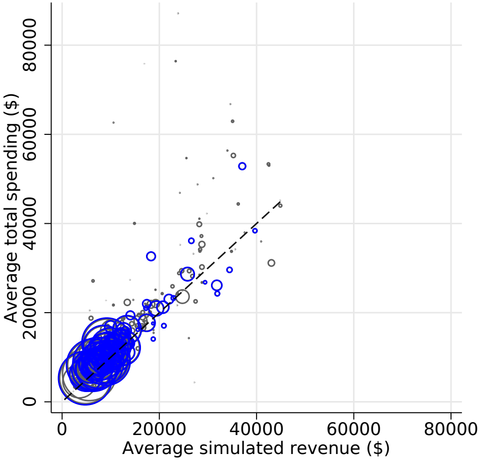
	Panel A					
Dependent Variable:	Fraction of Class Tiered Specialty or Higher					
Selection Incentive Variable:	Ratio (Cost/Revenue)		Difference (Cost - Revenue)		Ellis-McGuire Measure	
	(1)	(2)	(3)	(4)	(5)	(6)
Exchange X Selection incentive	0.046***	0.045**	0.044**	0.012	0.046***	0.010
	(0.014)	(0.022)	(0.017)	(0.014)	(0.018)	(0.015)
Exchange X Selection incentive ventile 20		0.006		0.300***		0.296***
		(0.105)		(0.076)		(0.089)
Therapeutic class FEs	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440

	Panel B					
Dependent Variable:	Fraction of Class Tiered Prior Auth./Step Therapy/Not Covered					
Selection Incentive Variable:	Ratio (Cost/Revenue)		Difference (Cost - Revenue)		Ellis-McGuire Measure	
	(7)	(8)	(9)	(10)	(11)	(12)
Exchange X Selection incentive	0.018*	0.031**	0.020*	0.008	0.018*	-0.002
	(0.011)	(0.016)	(0.011)	(0.011)	(0.010)	(0.014)
Exchange X Selection incentive ventile 20		-0.074		0.108		0.159**
		(0.092)		(0.083)		(0.078)
Therapeutic class FEs	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440

Main Result: Plots ▸ Back



Moral Hazard? We recode data to be matchable to Einav, Finkelstein, and Polyakova (2016) ▸ Back



Moral Hazard? No: Selection Incentive Uncorrelated with Elasticity ▸ Back