What Does Health Insurance Do?

AEA Continuing Education Program
CLASS #1

Matthew J. Notowidigdo ("Noto")
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University of Chicago Booth School of Business
Co-Director, Chicago Booth Healthcare Initiative
Co-Scientific Director, J-PAL North America
Research Associate, National Bureau of Economics Research

Course philosophy

- We will focus on recently-published papers, and we will try to minimize the overlap with the 2015 AEA Continuing Education lectures
  - 2015 webcasts: www.aeaweb.org/webcasts/2015/conted (lecturers: Jonathan Gruber, Adriana Lleras-Money, and Jonathan Skinner)
- We discuss cutting-edge research, but not at the level of detail as some other programs (e.g., "Summer Schools", NBER Summer Programs, etc.); we can give more details after lectures, during breaks, etc.
- Given our own research expertise, we focus primarily – but not exclusively – on healthcare and health insurance in the US
- Consult the reading list for the original research papers
- Questions always welcome!

About Me

- Born in Columbus, OH
- PhD: MIT
- After PhD: Chicago Booth ->

  Northwestern Econ ->

  (Back to) Chicago Booth
- Research interests: Health economics, Labor economics, Consumer/Household finance
- Co-editor at *AEJ-Policy*, 2017-2023
- New role at J-PAL North America!
- New Health Economics textbook!

About Me (J-PAL North America)

J-PAL North America's US Health Care Delivery Initiative (HCDI) supports randomized evaluations of strategies that aim to make health care delivery in the United States more efficient, effective, and equitable.

EVALUATION

Health Care Hotspotting in the United States

POLICY INSIGHT

The limited impact of US workplace wellness programs on health and employment-related outcomes

EVALUATION

The Effects of Voluntary Regulation on a Nationwide Medicare Bundled Payment Reform in the United States

J-PAL

ABDUL LATIF JAMEEL POVERTY ACTION LAB

Arnold Ventures

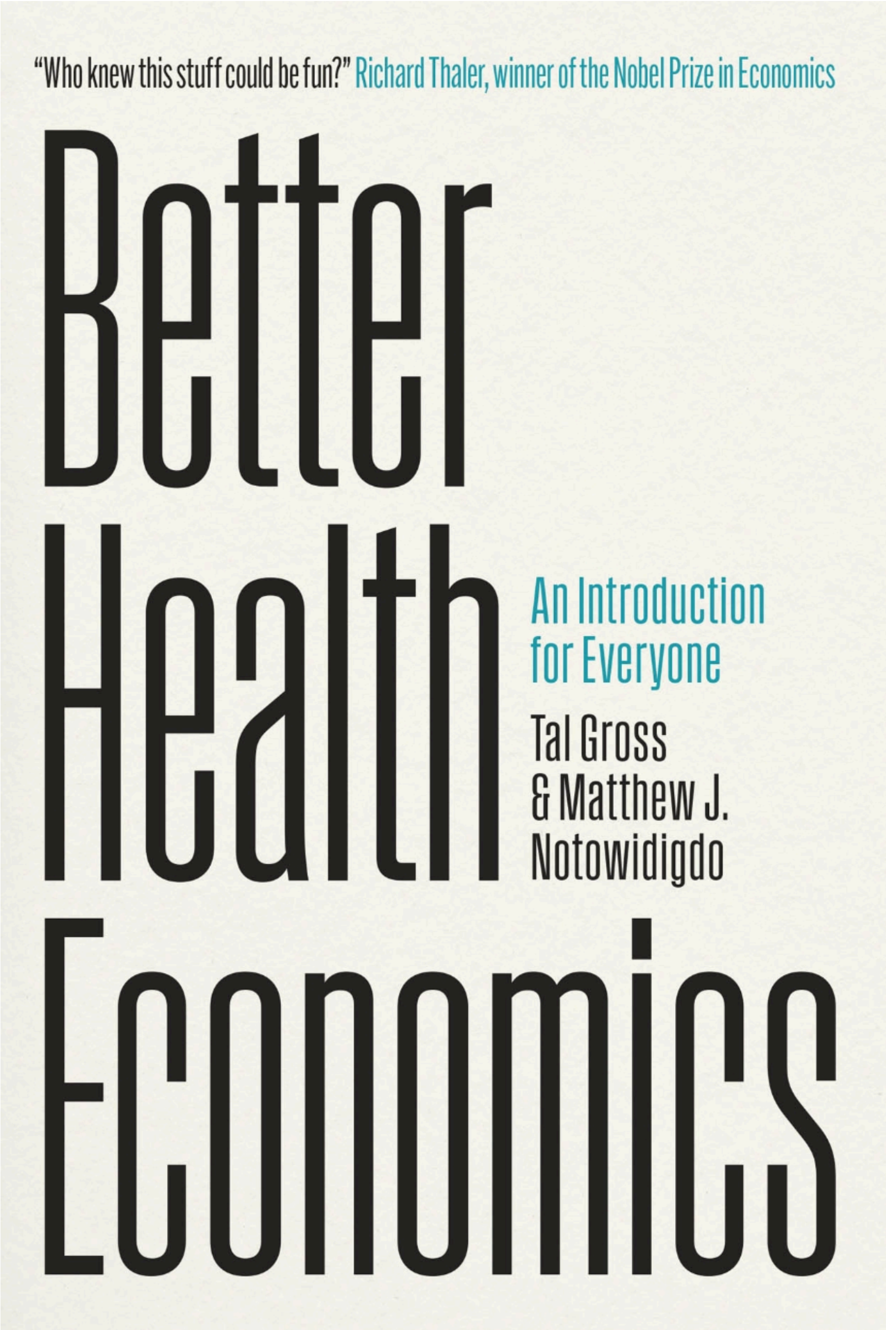
Robert Wood Johnson Foundation

NIH National Institute on Aging

Turning Discovery Into Health

https://www.povertyactionlab.org/initiative/us-health-care-delivery-initiative

About Me (New Book!)



https://press.uchicago.edu/ucp/books/book/chicago/B/bo208556491.html

Class #1 Outline

- Brief background on health insurance in the U.S.
- Brief review of the economics of uncertainty and the demand for insurance
- Review of research on the effects of health insurance on out-of-pocket medical spending, medical debt, and consumer bankruptcy
- Discussion of what health insurance does NOT do
- Why are people (still) uninsured?
- Conclusions and open questions

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Brief background on health insurance in US

- The U.S. government heavily subsidizes health insurance:
  - Largest federal tax expenditure: tax exclusion for employer-provided health insurance ($280B in 2018)
  - **Medicare** is second-largest line item ($580B in 2018)
  - **Medicaid** spending ($390B in 2018) >> SNAP, EITC ($70B, $60B)
- The **Affordable Care Act ("Obamacare")** further increased government spending on health insurance through new health insurance subsidies and the expansion of Medicaid
- What does this government spending do? Textbook answer: *"Health insurance allows risk-averse individuals to **smooth consumption** in response to large, unanticipated out-of-pocket medical expenses"*

*"No longer will illness crush and **destroy the savings** that they have so carefully put away over a lifetime"*

- President Johnson, signing Medicare into law in 1965

*"Because of this law, because of Obamacare, another 20 million Americans now know the **financial security** of health insurance."*

- President Obama, 2016 speech

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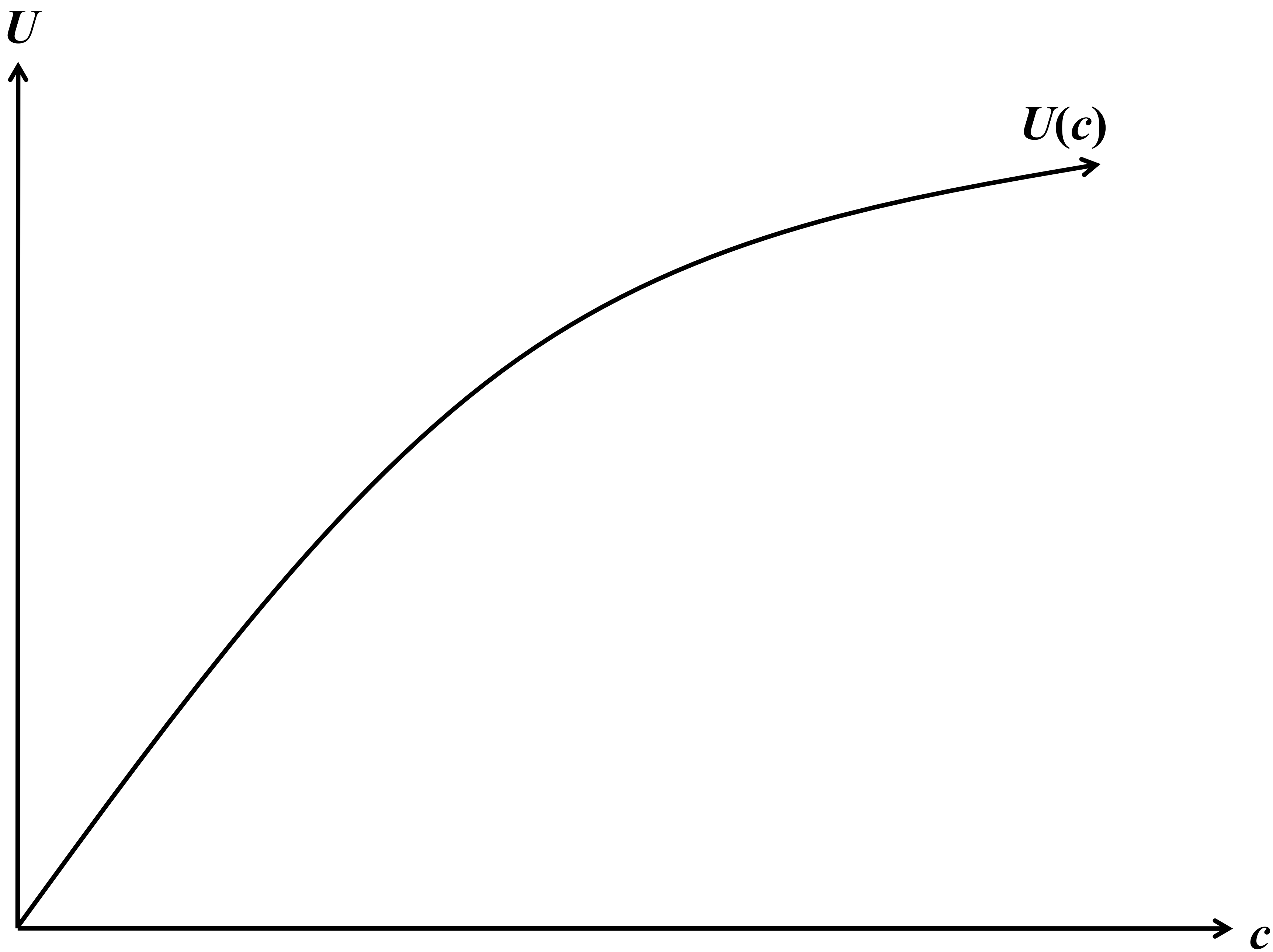
Utility function



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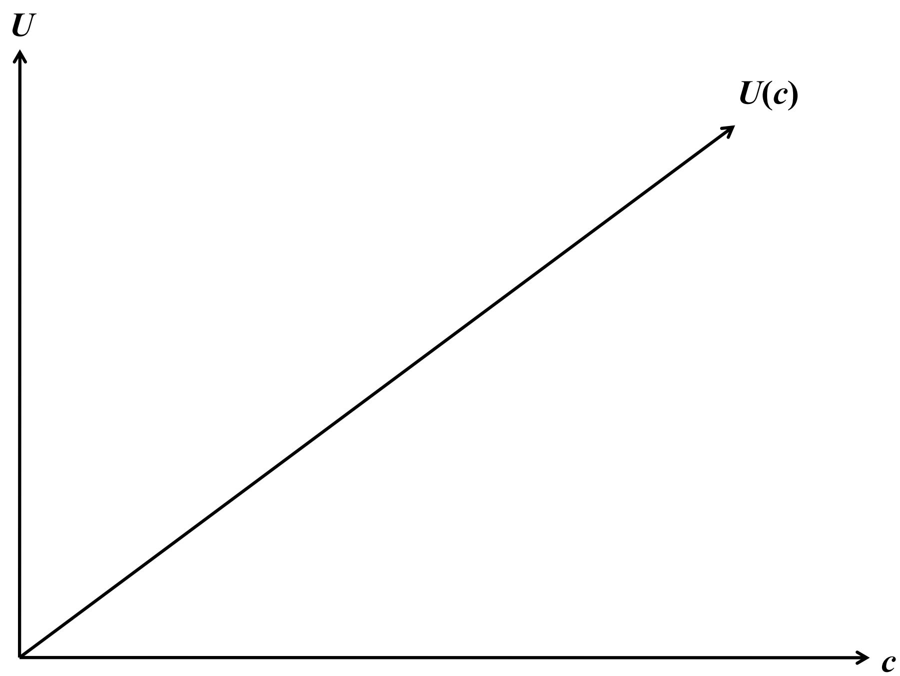
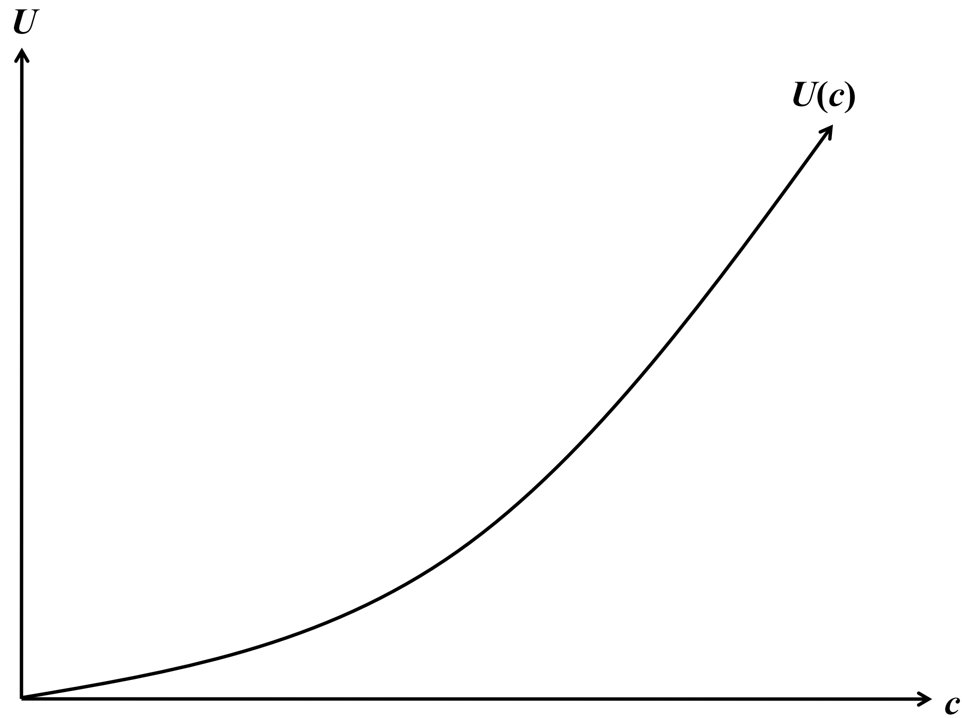
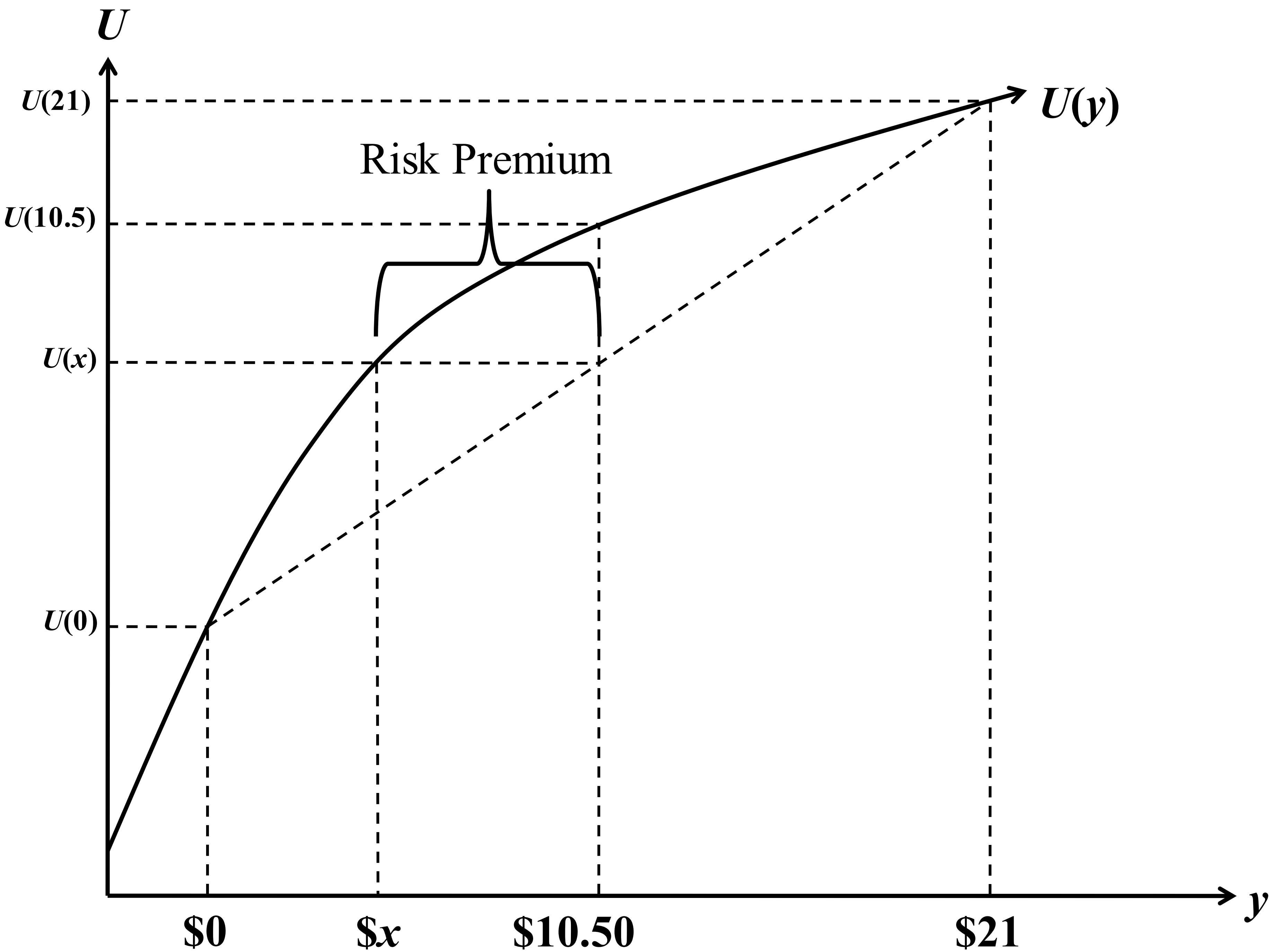


RISK NEUTRAL



RISK LOVING

Risk premium (RP) = EV – CE (where x = CE)



Calculating demand for insurance

Assume that an individual has income of \$100,000

The individual faces a risk of hospitalization of $p = 0.10$, which would lead to \$20,000 of medical expenses

Assume that the individual has a CRRA utility function

$$u(c) = (1/(1\text{-}\gamma))c^{1\text{-}\gamma}$$

where *c* is income net of out-of-pocket medical costs and γ is coefficient of relative risk aversion

QUESTION: How much would the individual be willing to pay for (full) insurance?

Calculating demand for insurance

Expected income net of out-of-pocket medical costs (*EV*):

0.9*($100,000) + 0.1*($100,000 - $20,000)

= $98,000

Certainty equivalent (*x*):

$$u(x) = 0.9*u(\$100{,}000) + 0.1*u(\$100{,}000 - \$20{,}000)$$

$$x^{1-\gamma} = 0.9*(\$100{,}000)^{1-\gamma} + 0.1*(\$80{,}000)^{1-\gamma}$$

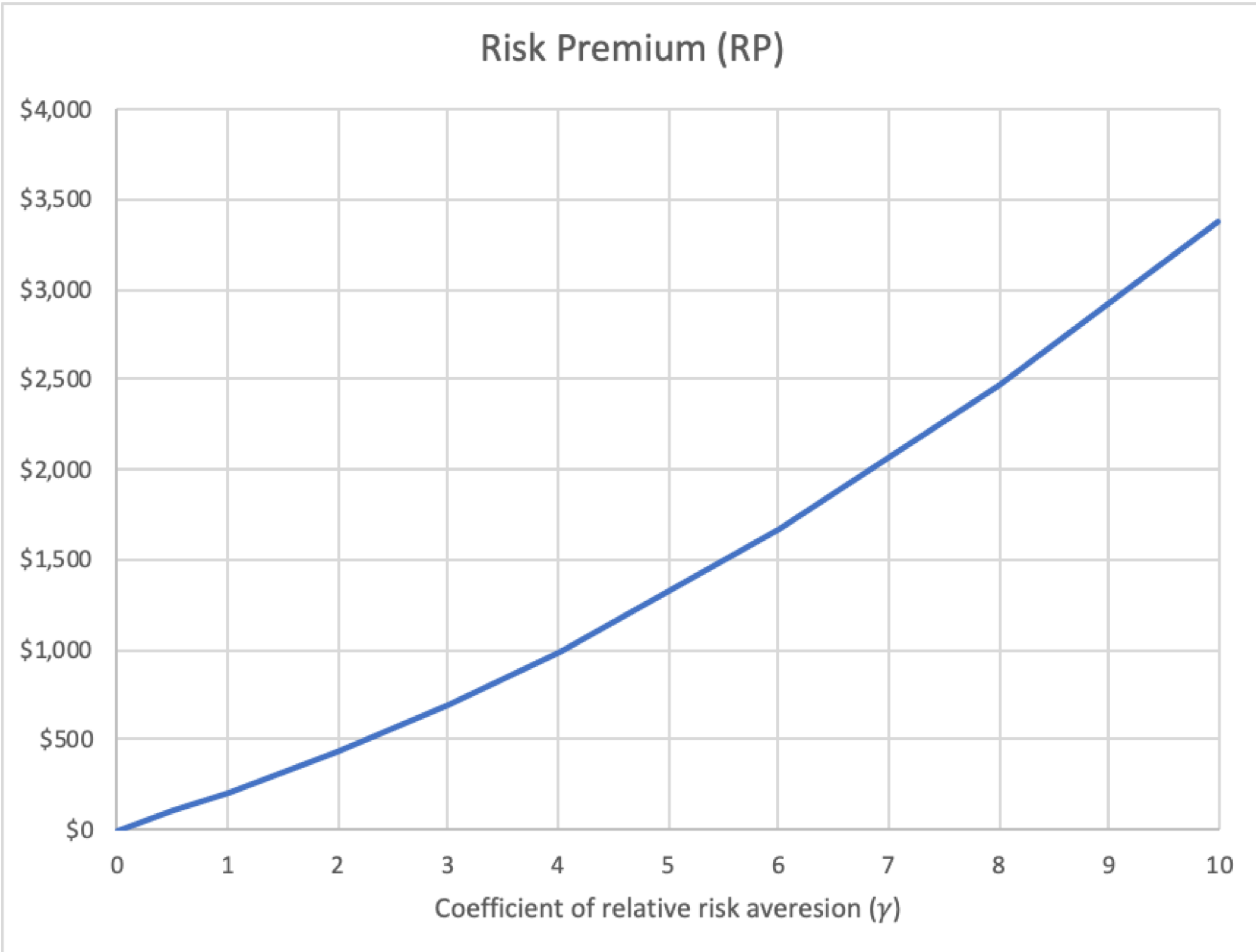
$$x = [\ 0.9*(\$100{,}000)^{1-\gamma} + 0.1*(\$80{,}000)^{1-\gamma}\ ]^{1/(1-\gamma)}$$

$$x = \$97{,}560.96 \text{ (at } \gamma = 2)$$

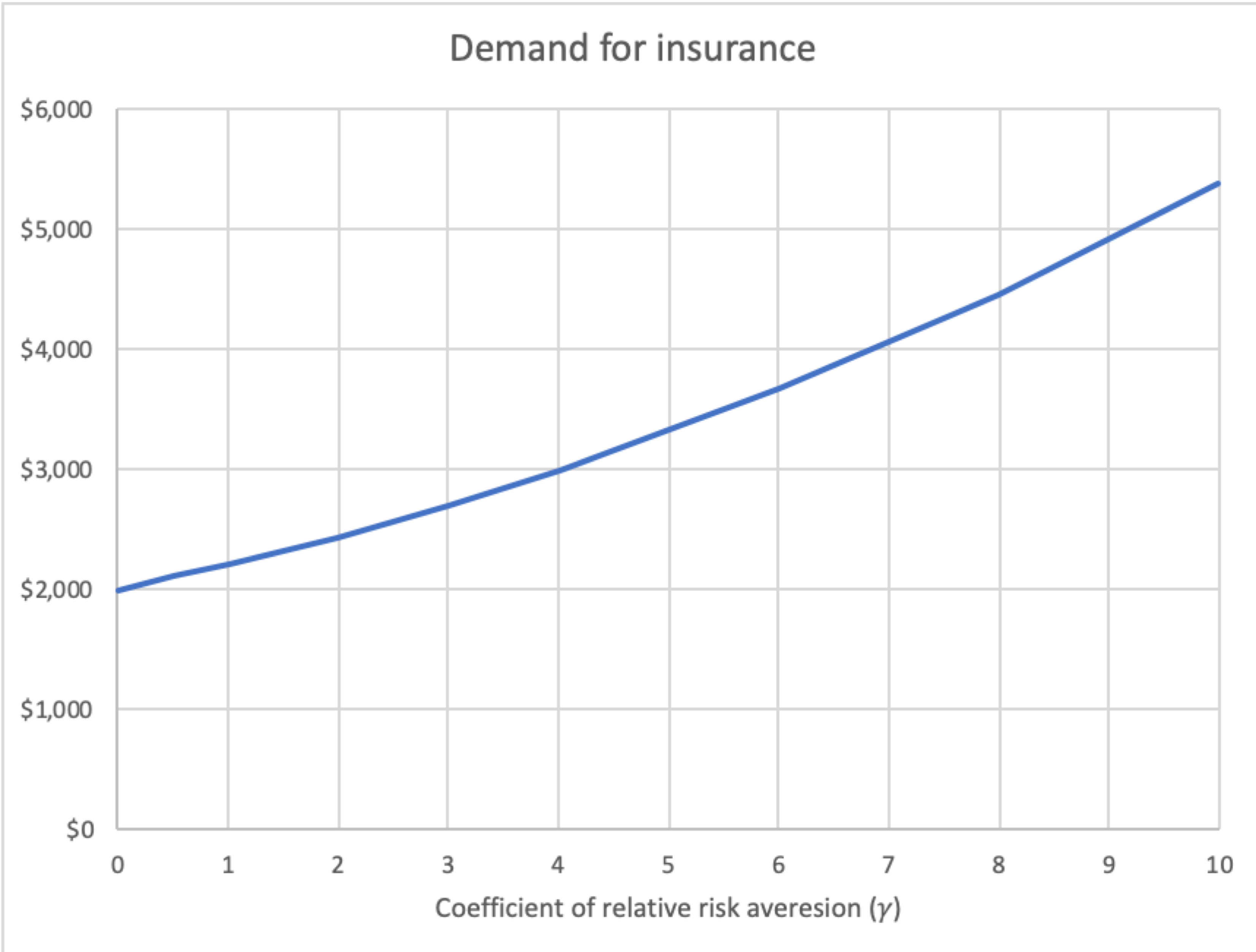
Risk premium (*RP = EV - CE*):

***RP* = $98,000 - $97,560.96 = $439.04**

Risk premium and risk aversion



Demand for insurance and risk aversion



Optimal insurance contract

Same setup: y = \$100,000, CRRA utility, risk of hospitalization of $p = 0.10$ which leads to \$20,000 of medical expenses (regardless of insurance status or the generosity of insurance)

Now assume a monopolist insurer chooses a take-it-or-leave-it price offer **(*p*)** and **coinsurance rate (*s*)**, which is the share of the medical expenses covered by the insurer

Proposition: Monopolist's profit-maximizing choice is to offer full insurance contract ($s = 1$) and choose price p to equal consumer's demand for full insurance contract

(See Einav-Finkelstein-Polyakova *AEJ-Policy* 2018 paper)

(Possible intuition from monopolist designing optimal two-part tariff)

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Health insurance and financial well-being

Finkelstein and McKnight *JPubE* 2008 study of the introduction of Medicare

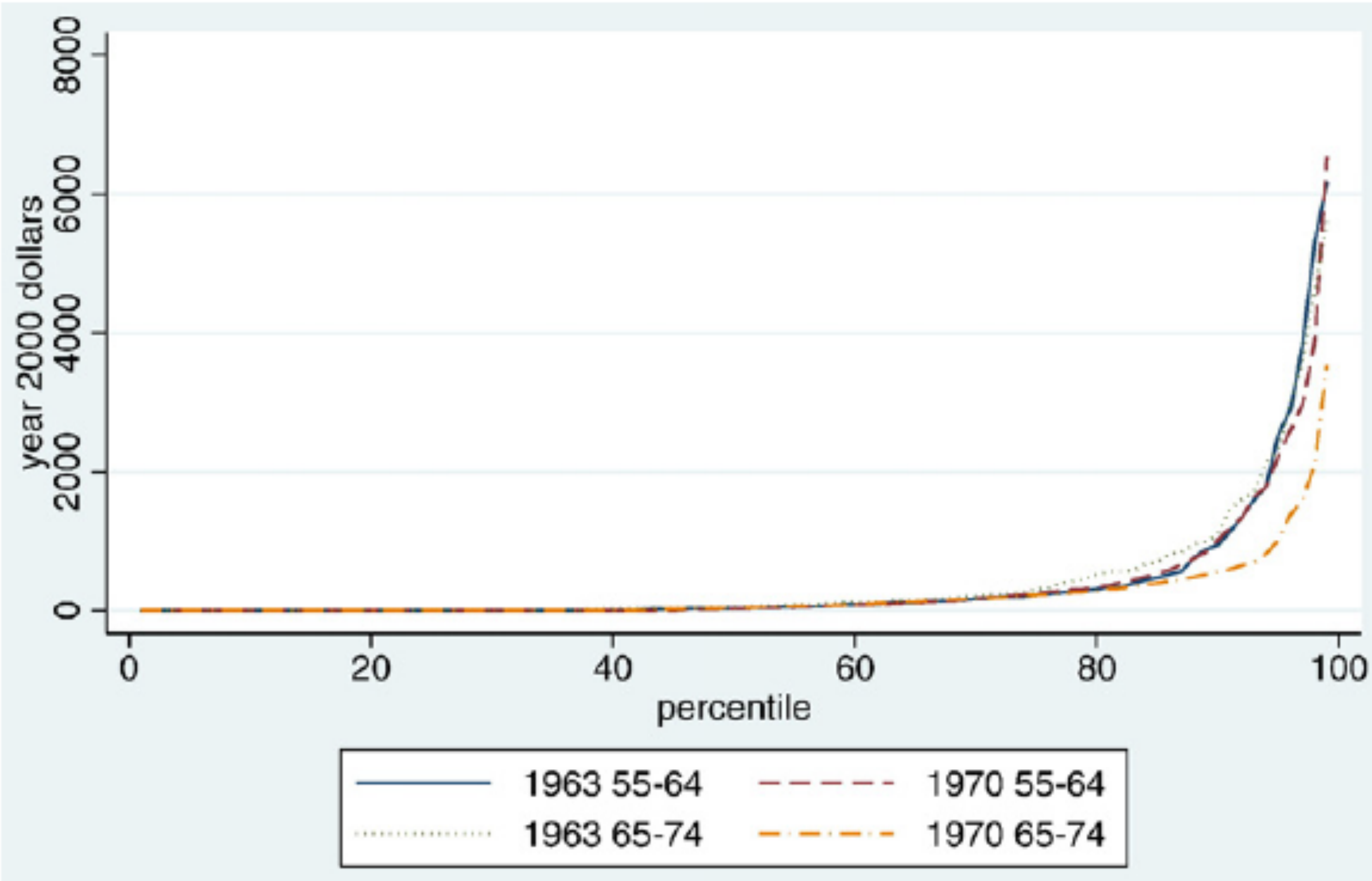


Fig. 6. Centiles of Medicare-eligible out of pocket spending by age group and year.

Health insurance and financial well-being

Finkelstein and McKnight *JPubE* 2008 study of the introduction of Medicare

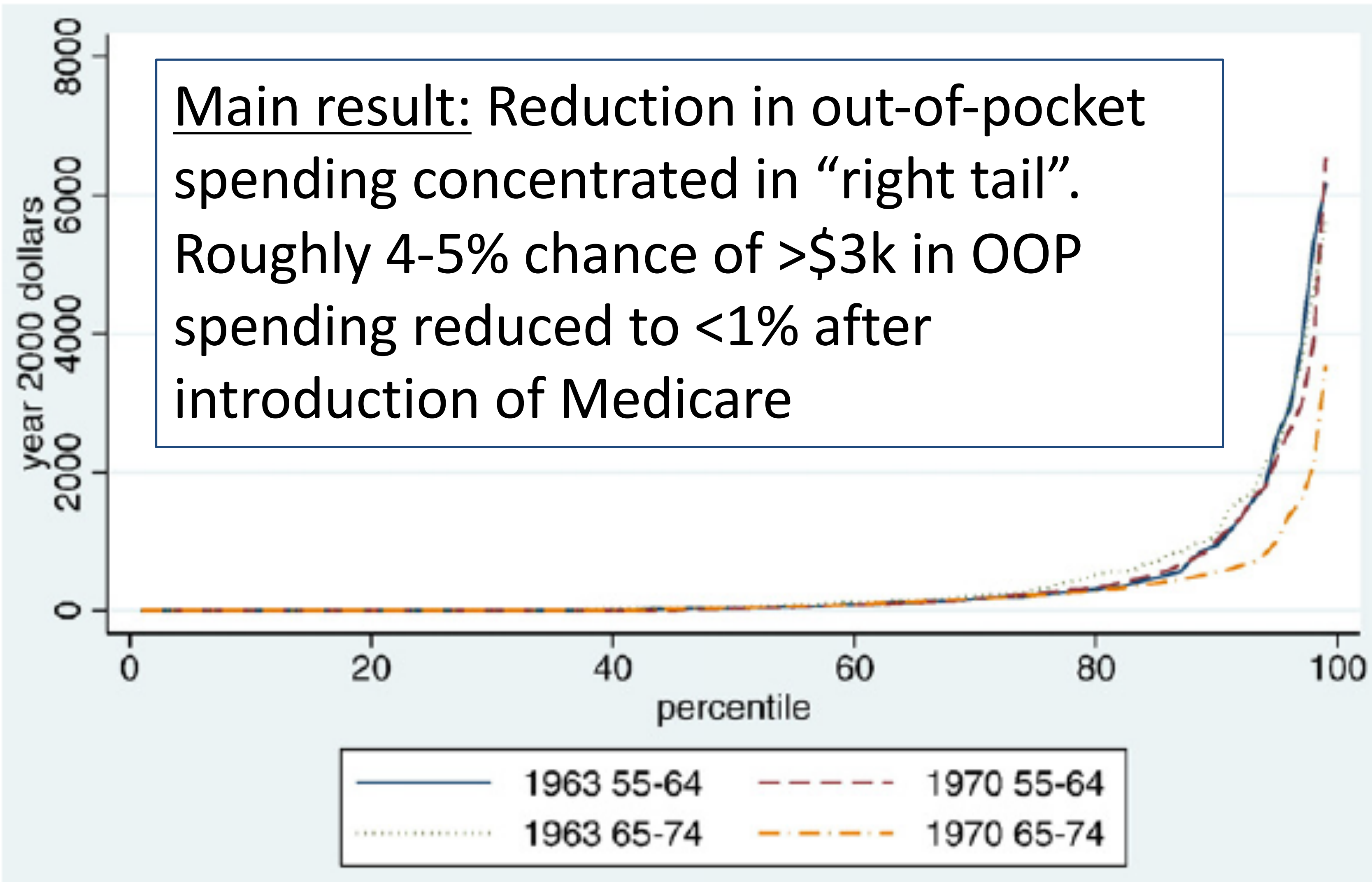


Fig. 6. Centiles of Medicare-eligible out of pocket spending by age group and year.

Health insurance and financial well-being

My research using data from CA (**Dobkin et al. 2018 AER**):

- Large sample of hospital admissions 2003-2007 [OSHPD] **linked** to consumer credit reports 2002-2011 [TransUnion]
- 380,000 insured adults (21-64), 150,000 uninsured adults (21-64), 400,000 elderly adults (65+), >5M credit reports
- Hospital discharge data: demographics (age, gender, race, ethnicity), date of admission, length of stay, diagnosis codes
- Credit report data: credit score, credit limits, auto loans, mortgage details, liens, foreclosures, bankruptcy, unpaid bills

Consumer credit reports in the US

Experian
A world of insight

Experian Credit Report and VantageScore®

Personal Information

Best Name	Other Name(s)	Social Security Number
JONATHAN QUINCY CONSUMER	JACK CONSUMER; JOHN SMITH	SSN MATCHES

Best Address	Other Address(es)	
32 BROOK ST PATCHOGUE, NY 11772-3825	555 N 1ST ST NEW HYDE PARK, NY 11040-2819	PO BOX 276 NEW HYDE PARK, NY 11040-0248

Best Employer	Other Employer
DEX MEDIA	DEX

Credit Score

Score & Risk Model	Score Factors
723 VantageScore® 3.0 (Score range: 300-850)	1. TOTAL OF ALL BALANCES ON BANK CARD OR REVOLVING ACCOUNTS IS TOO HIGH 2. YOUR LARGEST CREDIT LIMIT ON OPEN BANKCARD OR REVOLVING ACCT IS TOO LOW 3. YOU HAVE TOO MANY INQUIRIES ON YOUR CREDIT REPORT. 4. THE BALANCES ON YOUR ACCOUNTS ARE TOO HIGH COMPARED TO LOAN LIMITS

Account History

Real Estate Accounts

GREENPOINT MORTGAGE

Open Date	Original Amount	Past Due	Scheduled Payment	Current Balance
02/15/2002	$157,500		$2,659	$10,336

Account Condition: Open
Account Type: Conventional Real Estate Loan, Including Purchase Money First
Payment Status: Current
Account Terms: 20 Year
Payment History: (Up to 25 months)

Mar	Feb	Jan	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar	Feb	Jan	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar
13	13	13	12	12	12	12	12	12	12	12	12	12	12	12	11	11	11	11	11	11	11	11	11	11
C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C

Installment Accounts

BPD INTERNATIONAL BK

Open Date	Original Amount	Past Due	Scheduled Payment	Current Balance
02/15/2010	$13,523		$300	$6,622

Account Condition: Open
Account Type: Secured Loan
Payment Status: Current/was 30 days past due
Account Terms: 60 Month
Payment History: (Up to 25 months)

Feb	Jan	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar	Feb	Jan	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar	Feb
13	13	12	12	12	12	12	12	12	12	12	12	12	12	11	11	11	11	11	11	11	11	11	11	11
C	C	C	C	C	C	C	C	C	C	C	C	1	-	C	C	C	C	C	C	C	C	C	C	C

JAGUAR CREDIT

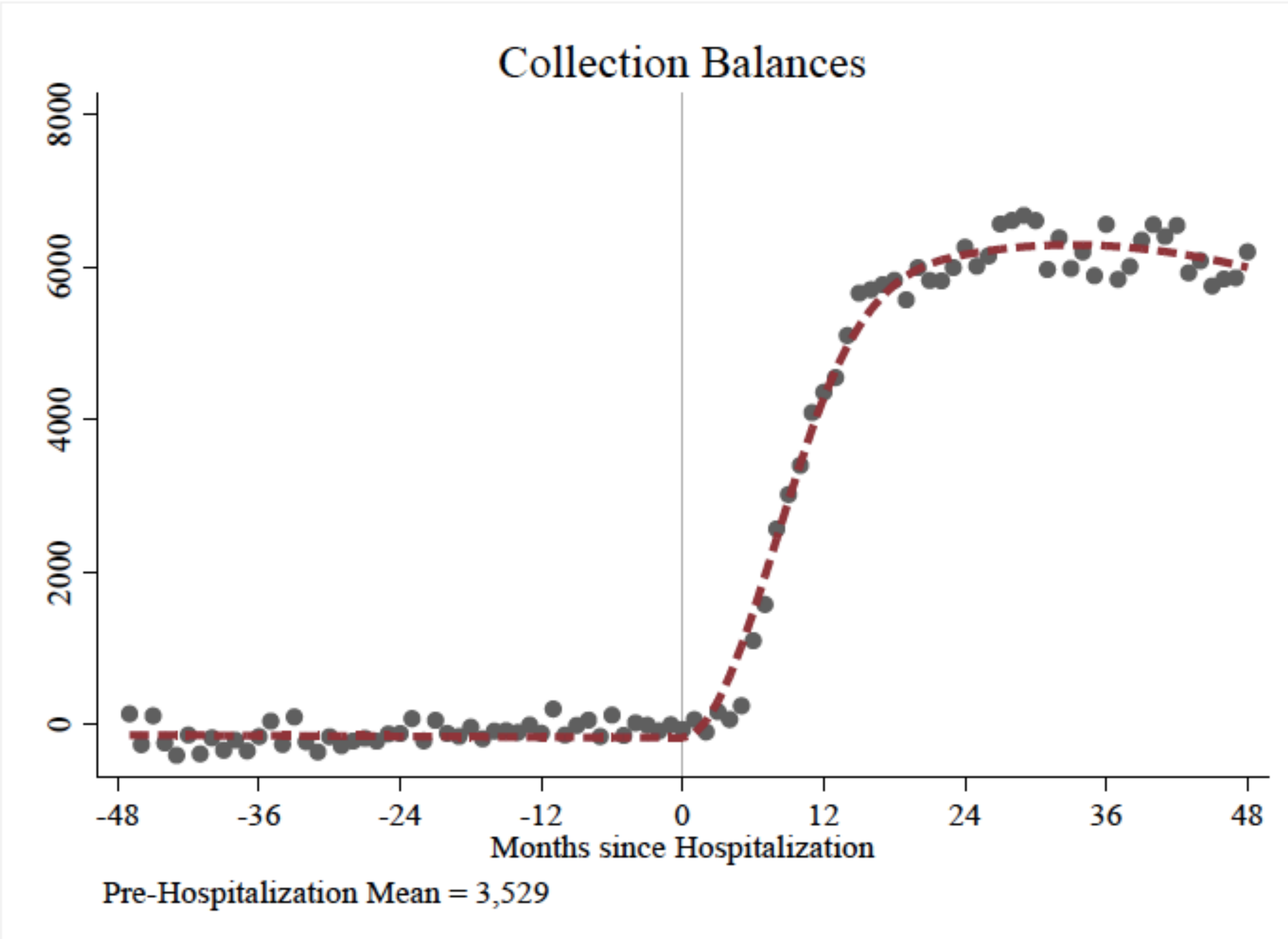
Open Date	Original Amount	Past Due	Current Balance
02/28/2009	$20,376		

Account Condition: Paid/zero balance
Account Type: Auto Lease
Payment Status: Current
Account Terms: 36 Month
Payment History: (Up to 25 months)

Feb	Jan	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar	Feb	Jan	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar	Feb
12	12	11	11	11	11	11	11	11	11	11	11	11	11	10	10	10	10	10	10	10	10	10	10	10
B	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C

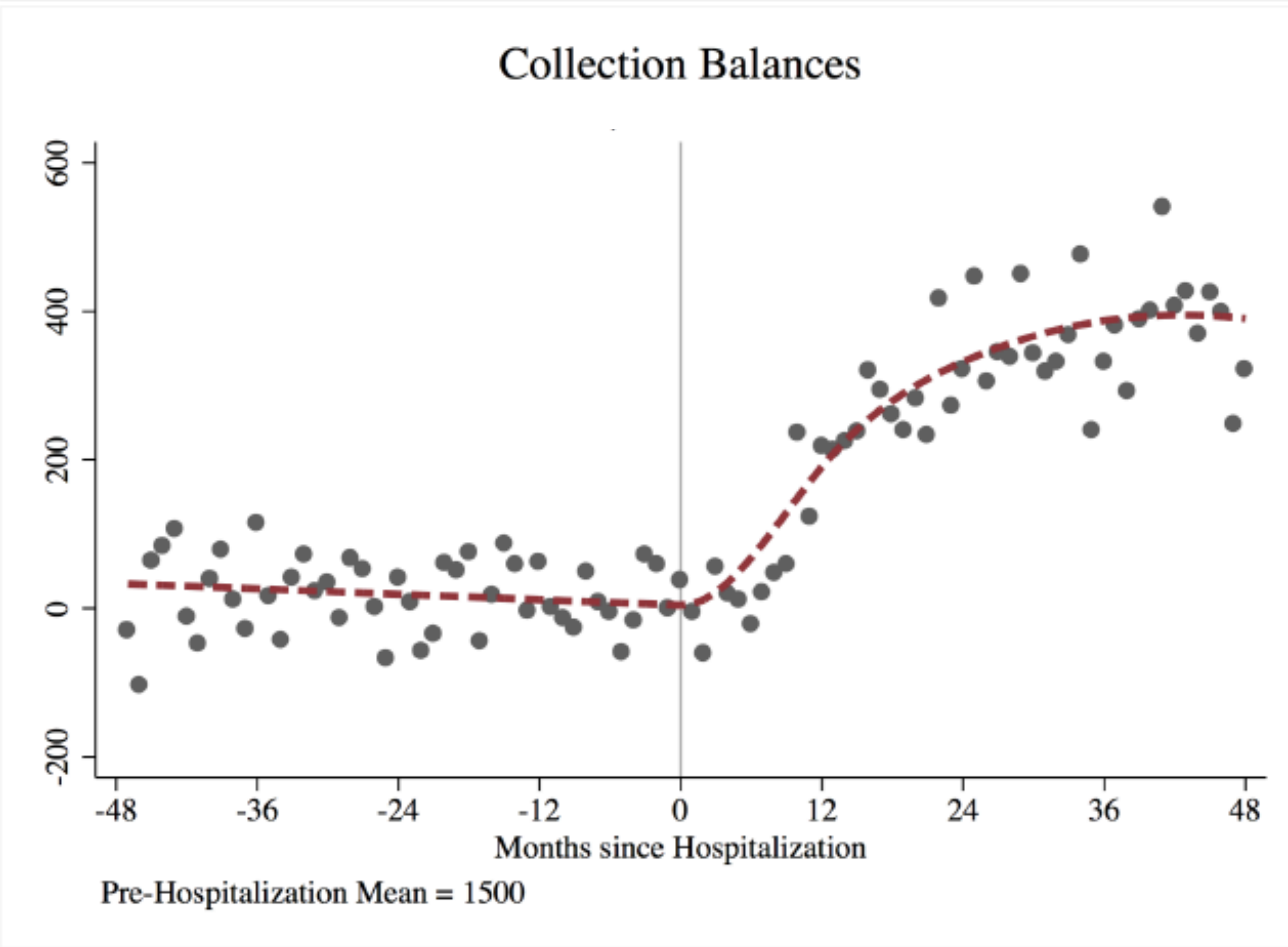
Health insurance and financial well-being

Dobkin et al. AER 2018 study of hospitalizations in CA **[uninsured sample]**

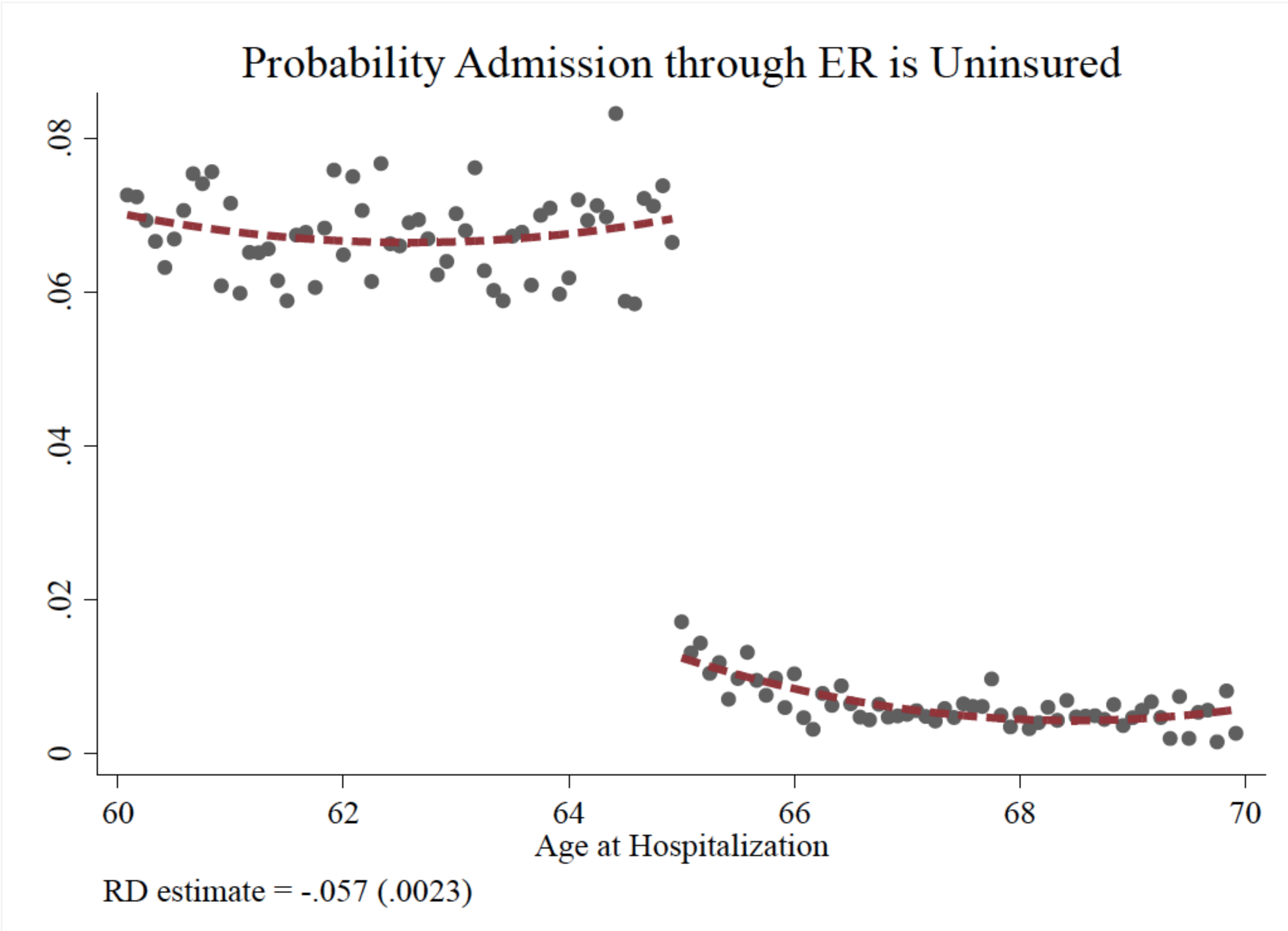


Health insurance and financial well-being

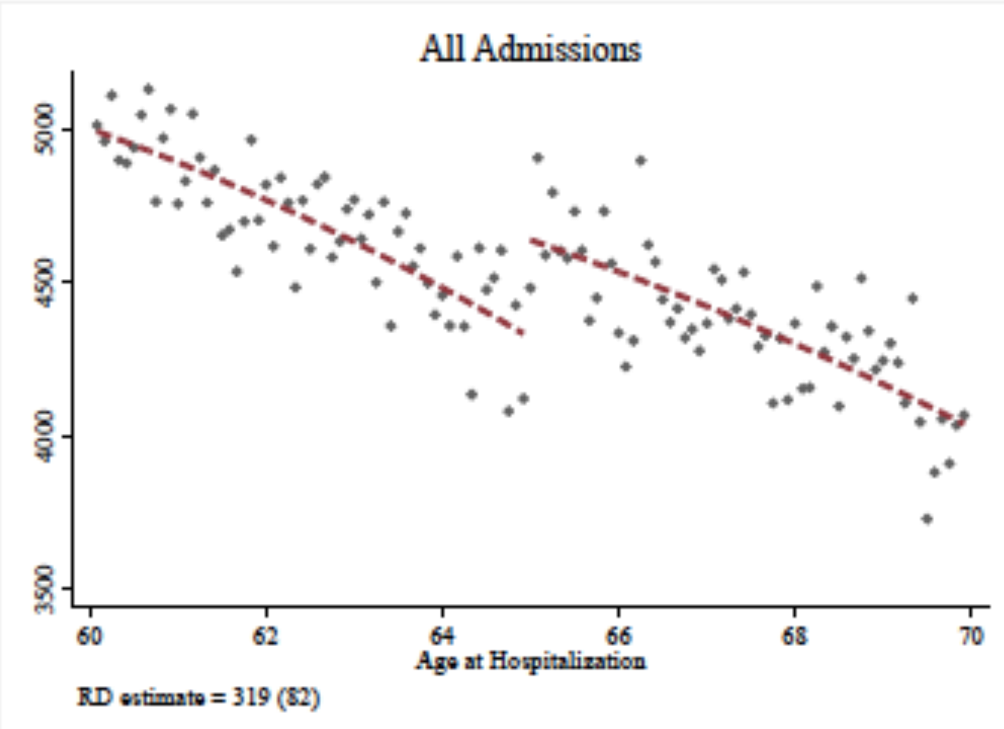
Dobkin et al. AER 2018 study of hospitalizations in CA **[insured sample]**

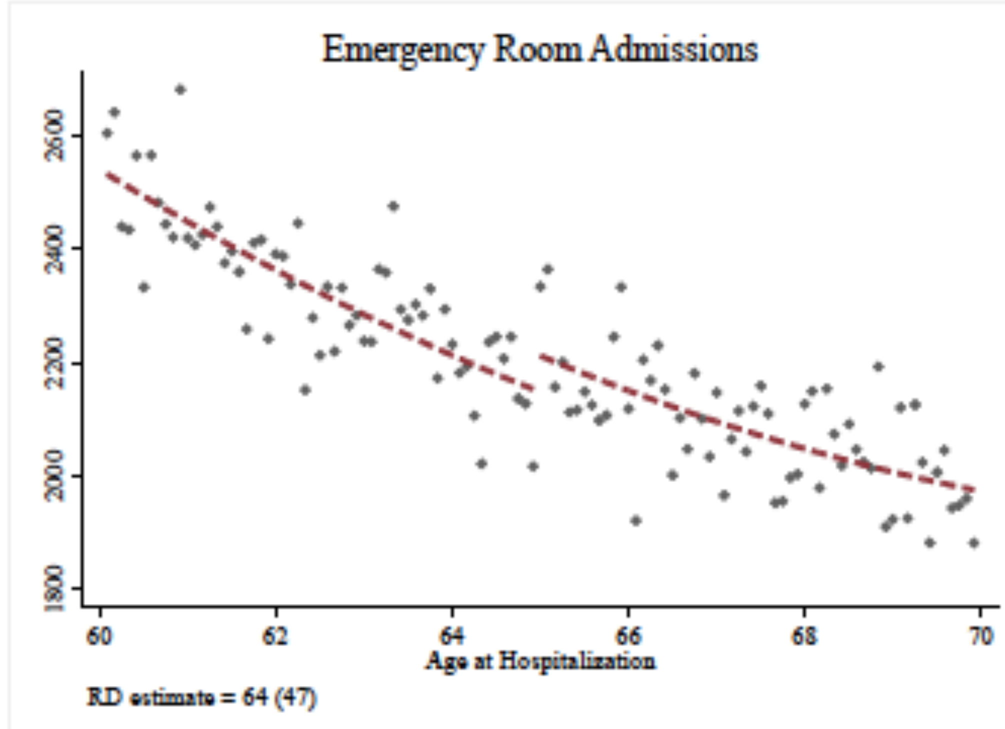


Health insurance and financial well-being

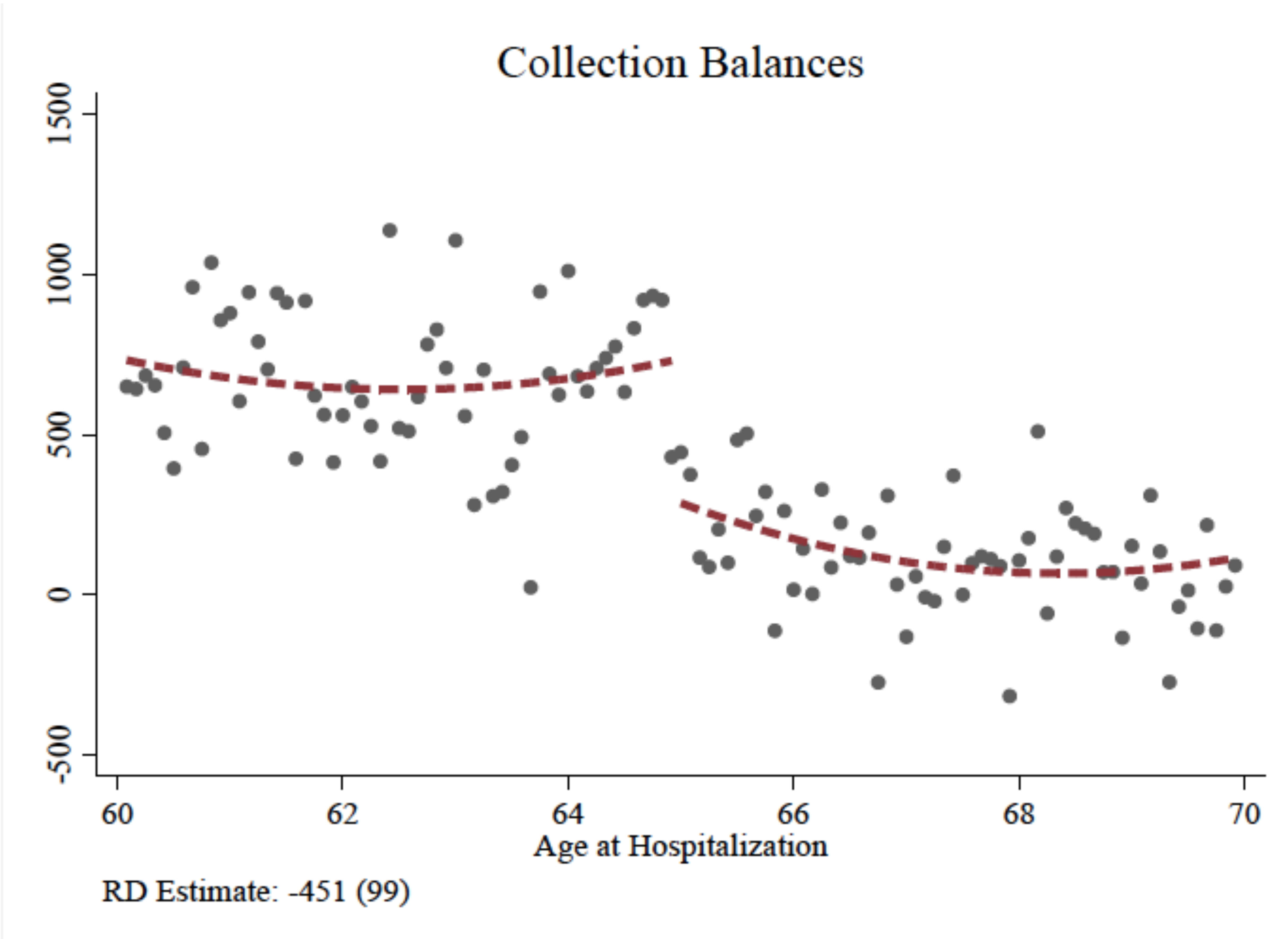


Distribution of hospital admissions by age in CA





Health insurance and financial well-being



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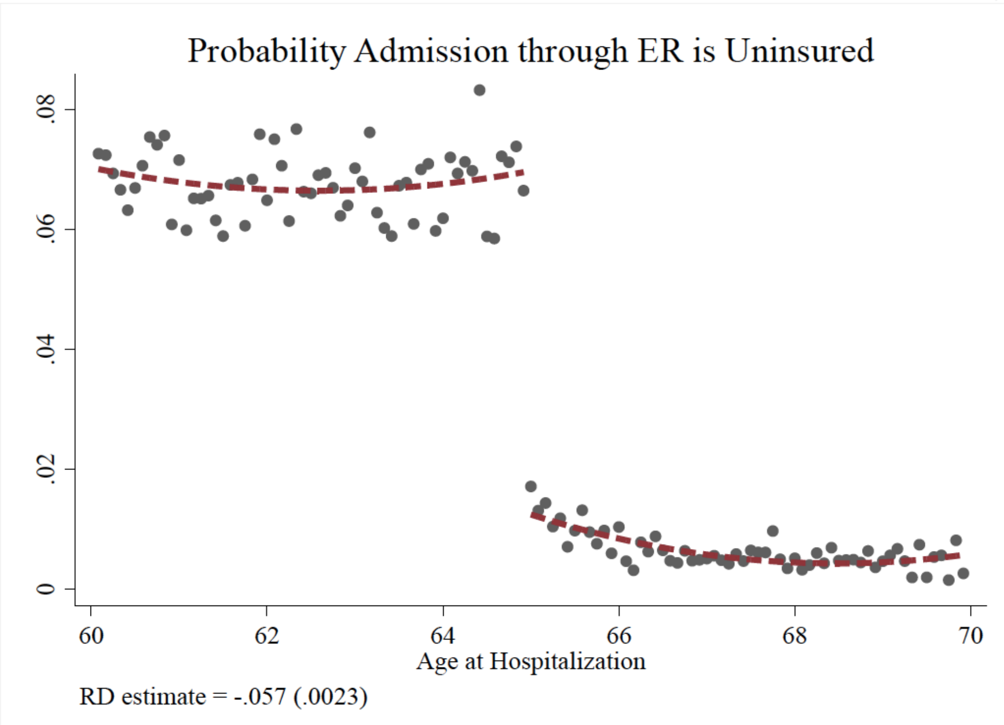
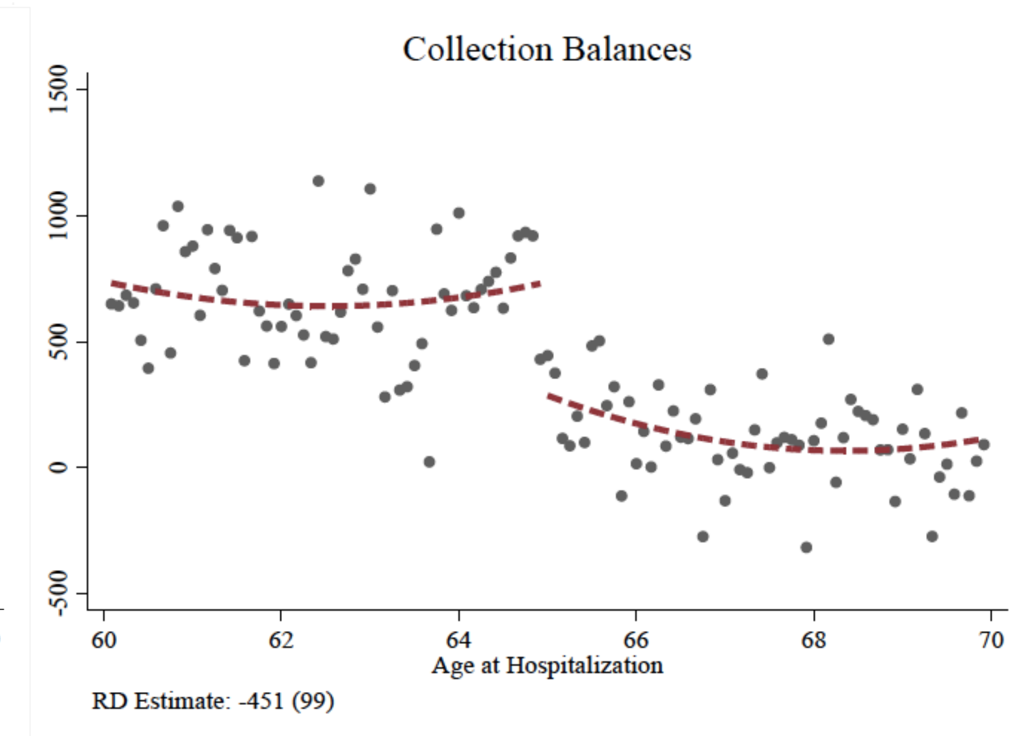


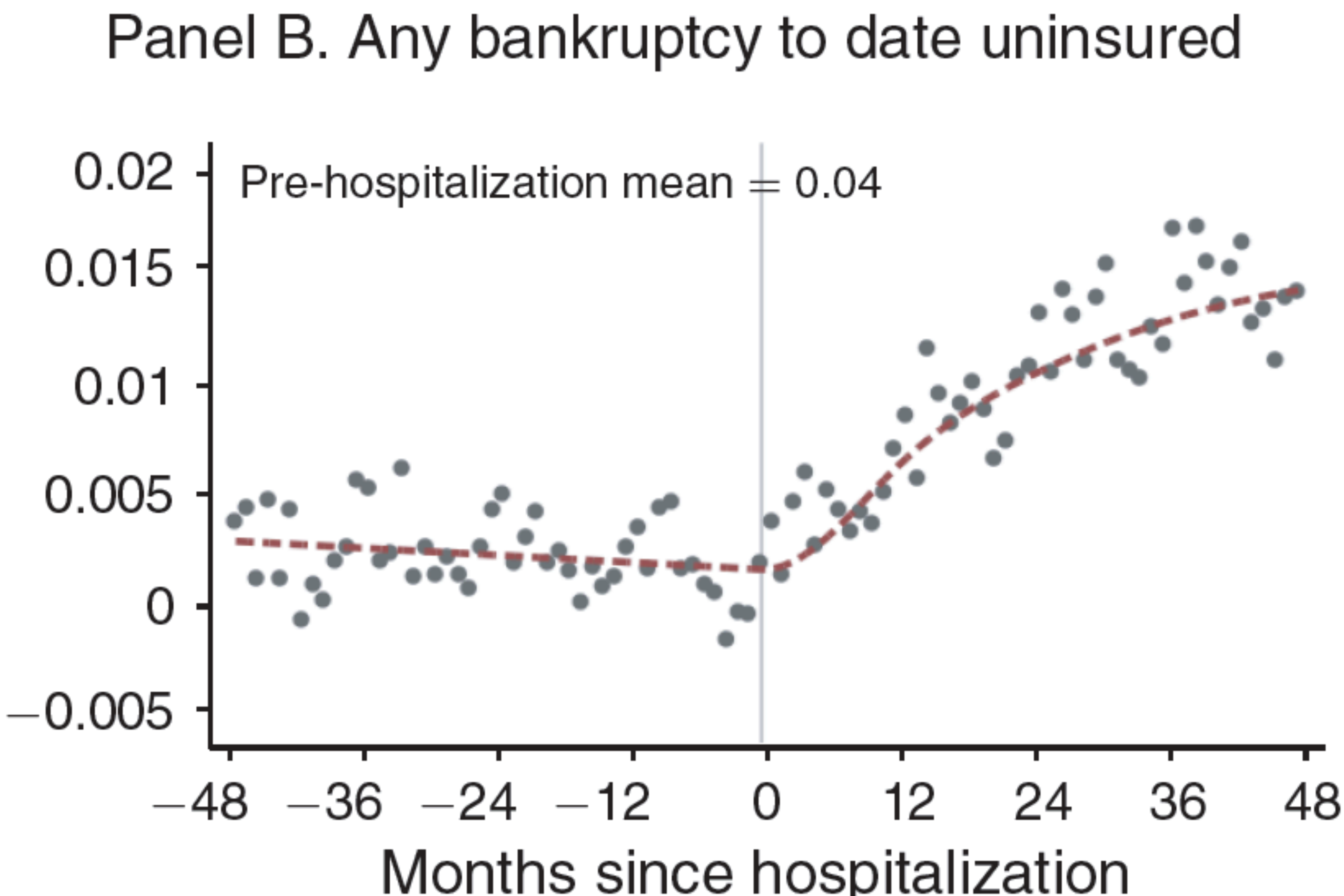


Implied IV estimate for collection balances:

-450/(-0.057) = $7,900

"Naive" DD comparing impact for prime-age insured and uninsured = $4,300

Health insurance and financial well-being



Health insurance and financial well-being

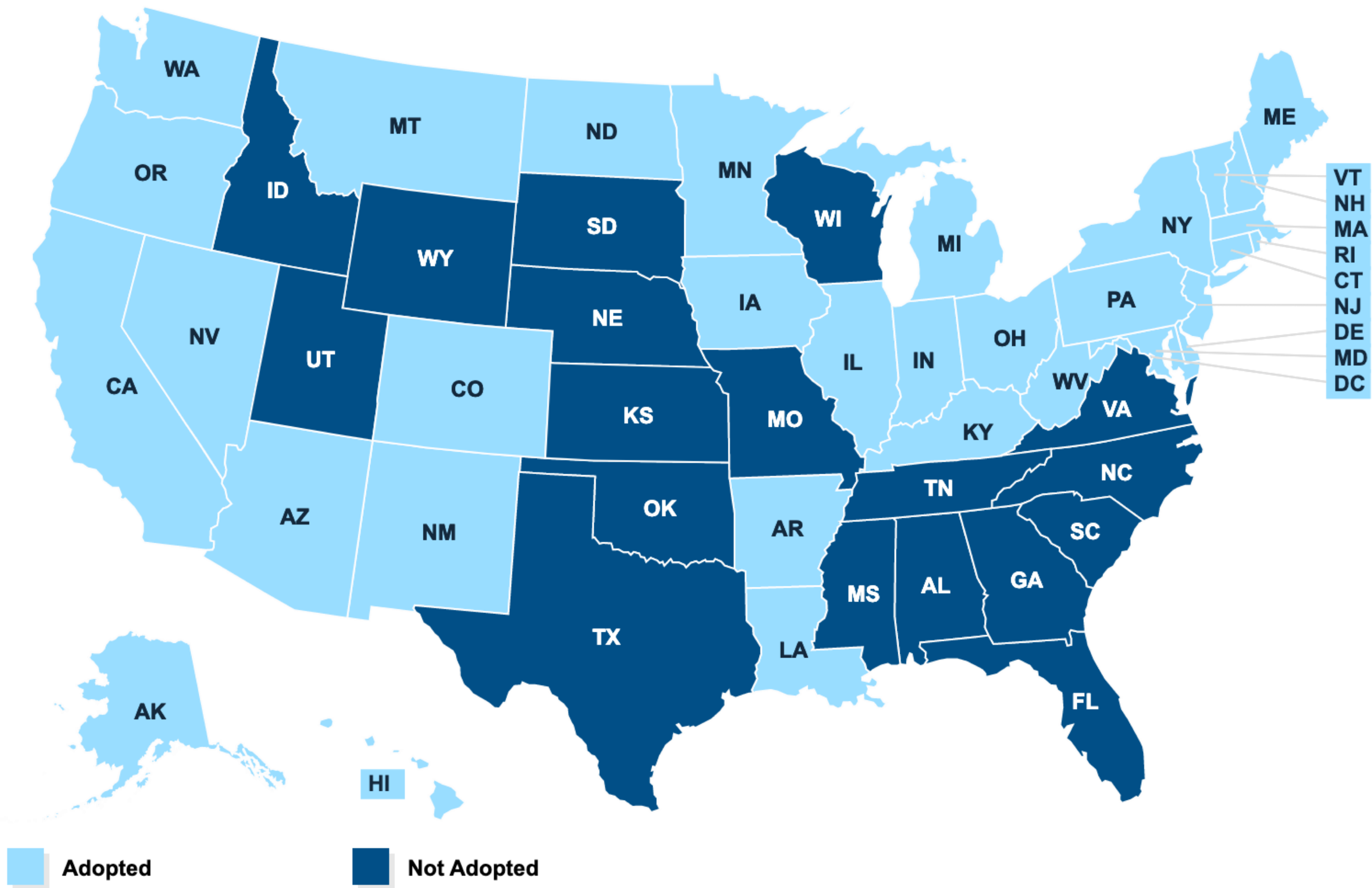
Additional evidence that health insurance improves financial well-being, reduces unpaid medical bills, and reduces the risk of filing for bankruptcy:

- Oregon Health Insurance Experiment (Finkelstein et al. *QJE*)

- Massachusetts health reform ["Romneycare"] (Miller and Mazumder *AEJ-Policy*)

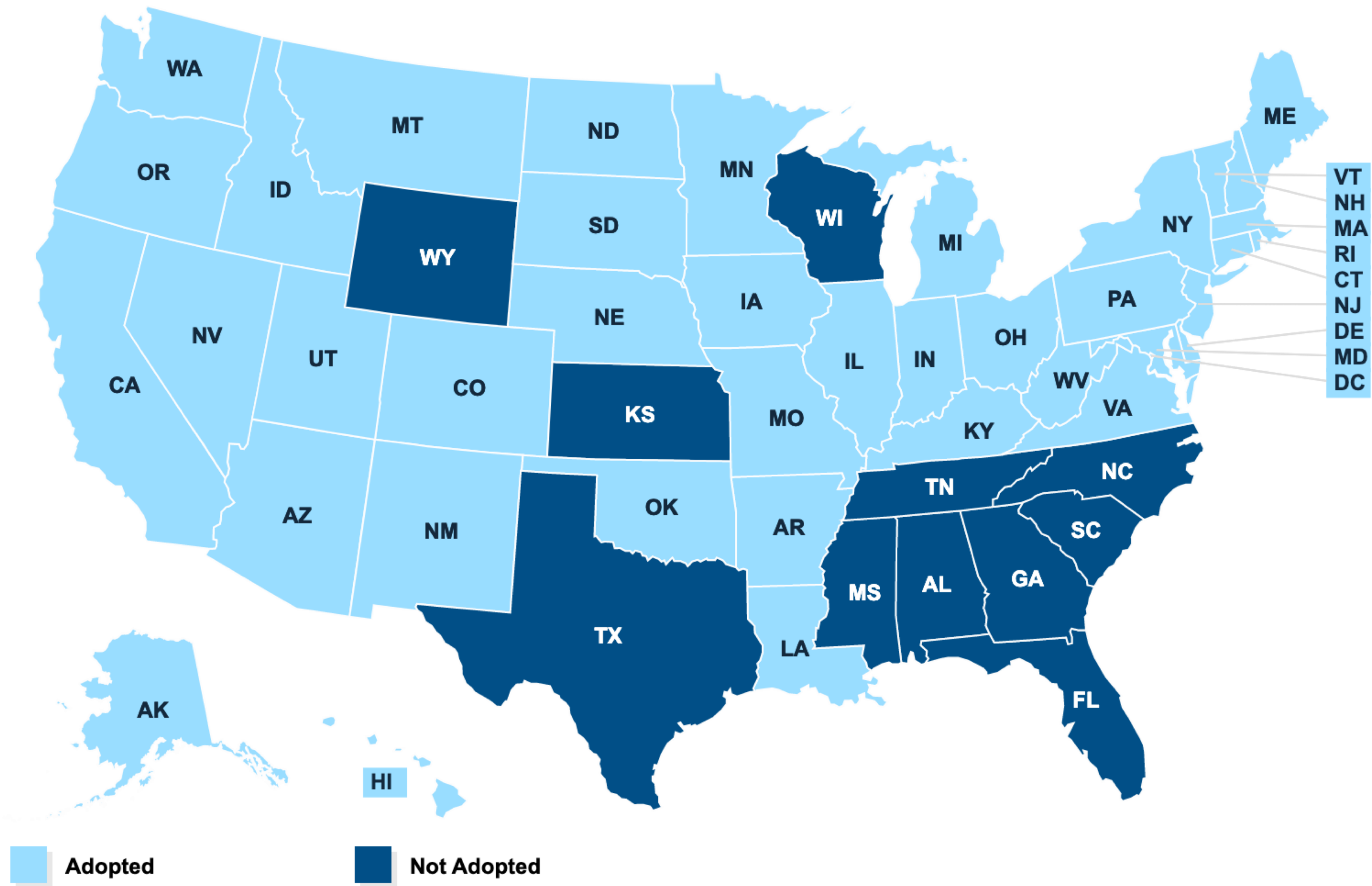
- Affordable Care Act ["Obamacare"] (Hu et al. *JPAM*)

Medicaid expansion (as of November 2017)



Source: https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/

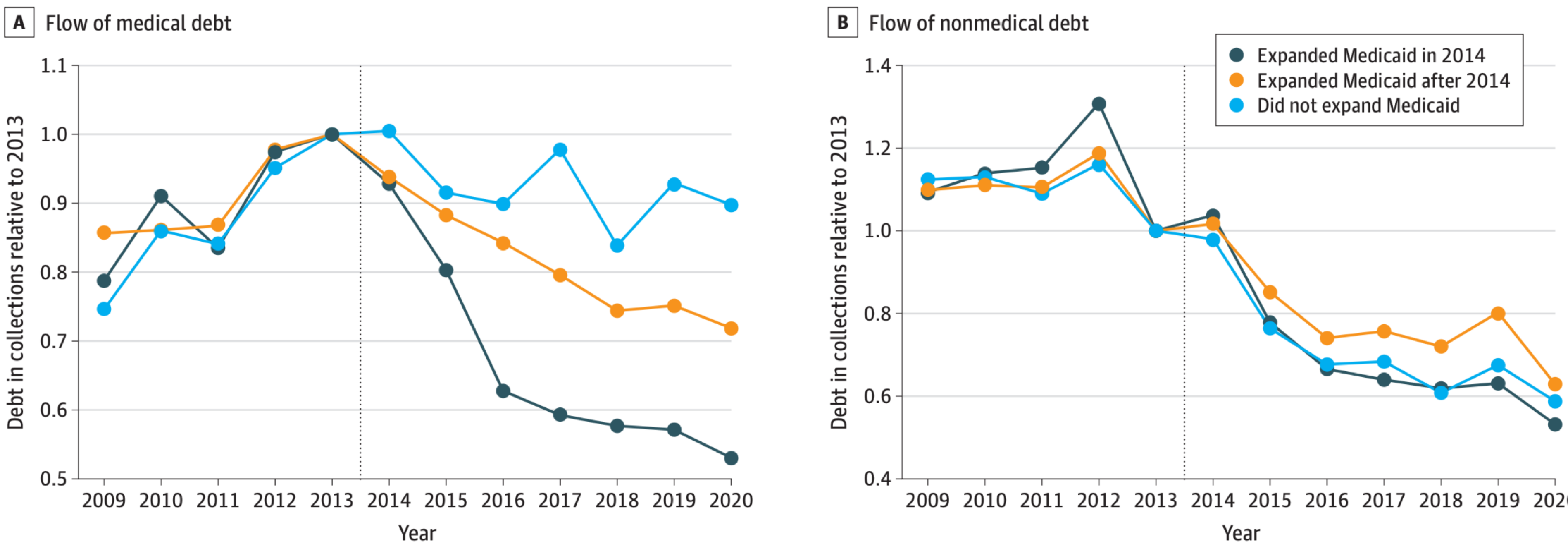
Medicaid expansion (as of December 2022)



Source: https://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/

Health insurance and financial well-being

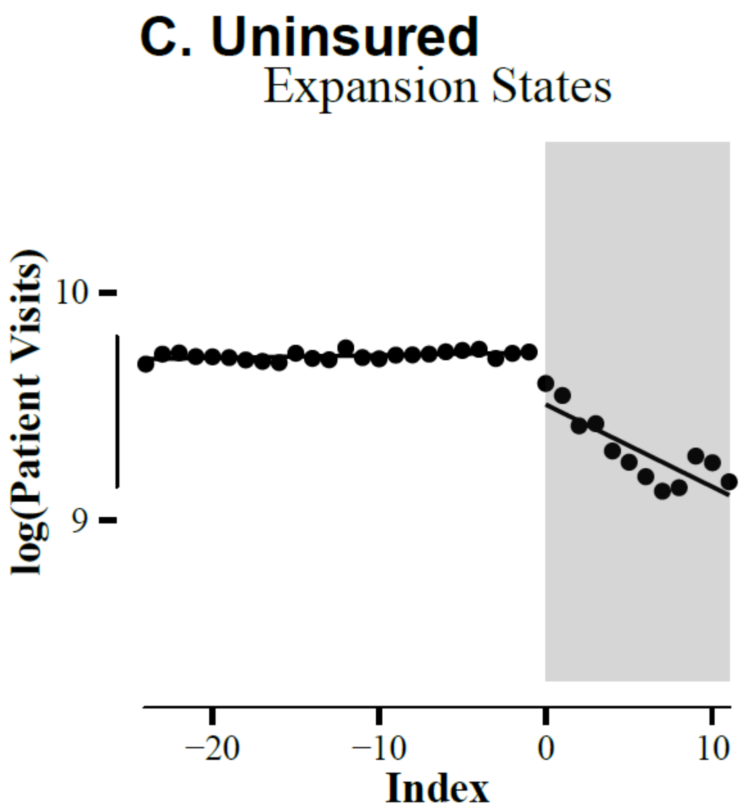
Figure 3. Trends in Medical and Nonmedical Debt in Collections by Medicaid Expansion Status

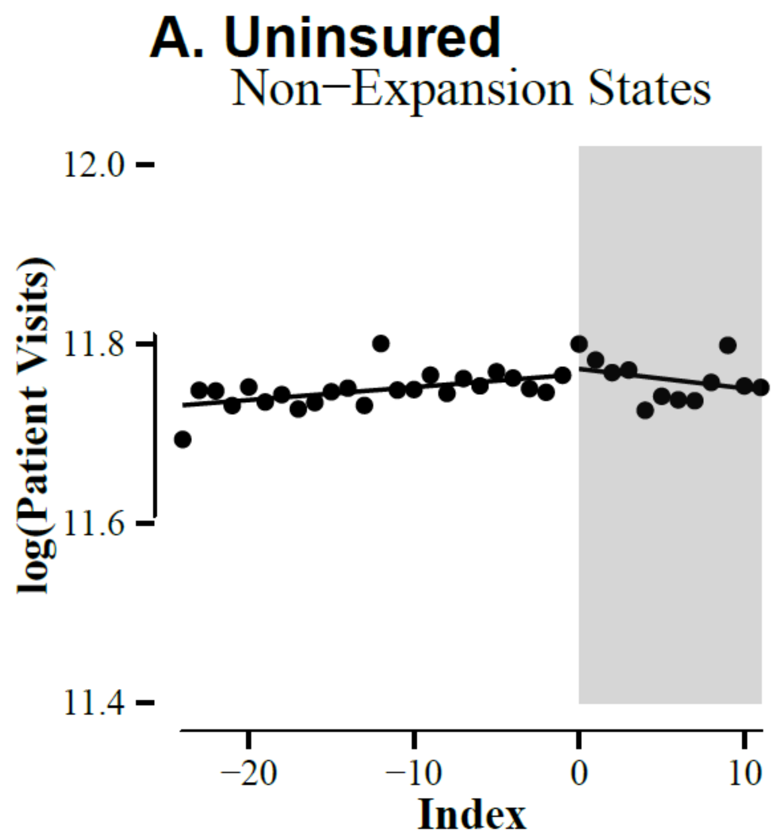


Source: https://jamanetwork.com/journals/jama/article-abstract/2782187

What else does health insurance do?

Change in **uninsured** ED visits





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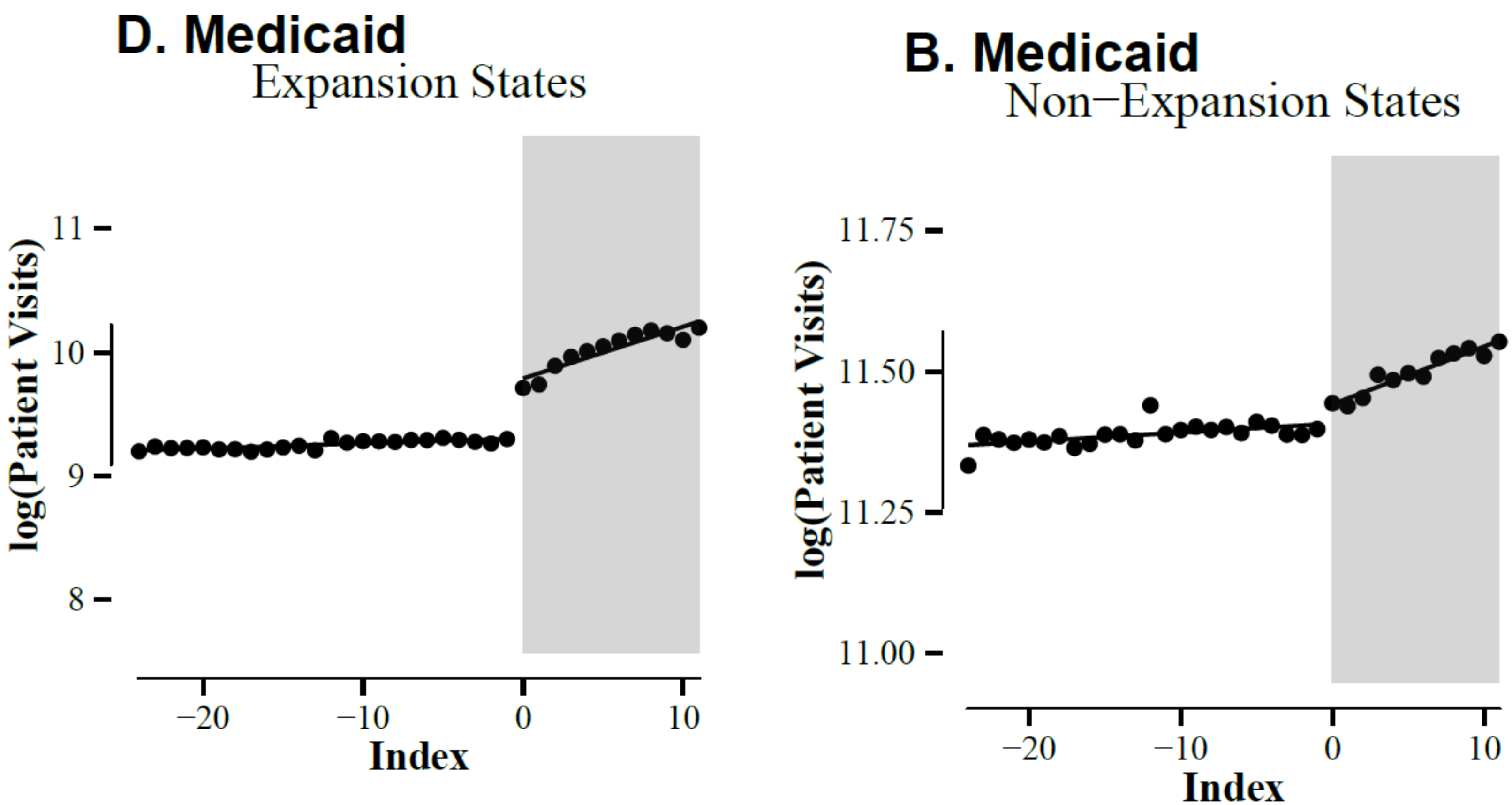


All Medicaid Expansions Are Not Created Equal: The Geography and Targeting of the Affordable Care Act*

October 2019

Craig Garthwaite
Northwestern University and NBER

John Graves
Vanderbilt University

Tal Gross
Boston University and NBER

Zeynal Karaca
Agency for Healthcare Research and Quality

Victoria Marone
Northwestern University

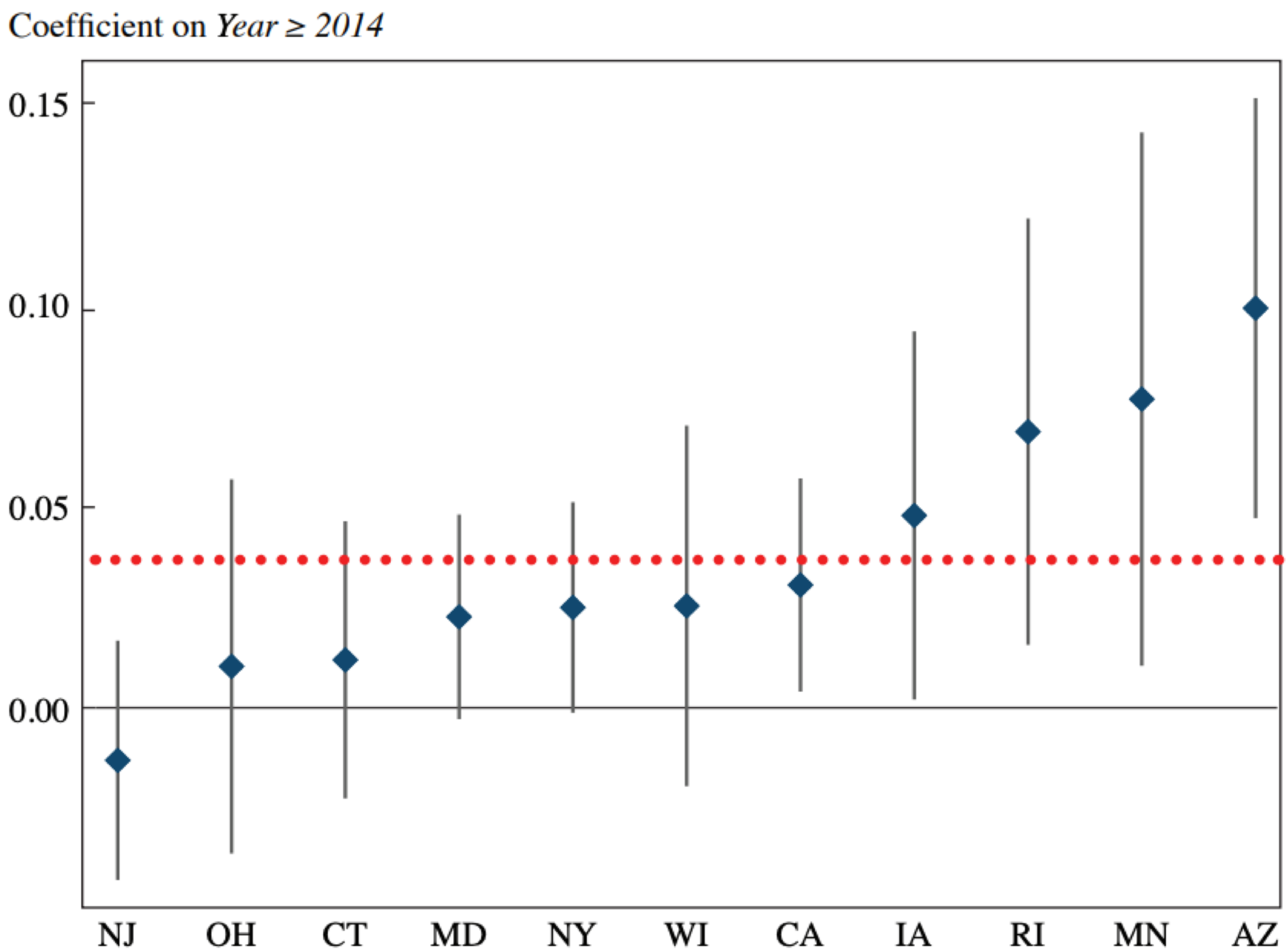
Matthew J. Notowidigdo
Northwestern University and NBER

Abstract

We use comprehensive patient-level discharge data to study the effect of Medicaid on the use of hospital services. Our analysis relies on cross-state variation in the Affordable Care Act's Medicaid expansion, along with within-state variation across ZIP Codes in exposure to the expansion. We find that the Medicaid expansion increased Medicaid visits and decreased uninsured visits. The net effect is positive for all visits, suggesting that those who gain coverage through Medicaid consume more hospital services than they would if they remained uninsured. The increase in emergency department visits is largely accounted for by "deferrable" medical conditions. Those who gained coverage under the Medicaid expansion appear to be those who had relatively high need for hospital services, suggesting that the expansion was well targeted. Lastly, we find significant heterogeneity across Medicaid-expansion states in the effects of the expansion, with some states experiencing a large increase in total utilization and other states experiencing little change. Increases in hospital utilization were larger in Medicaid-expansion states that had more residents gaining coverage and lower pre-expansion levels of hospital uncompensated care costs.

Heterogeneity in ACA Medicaid expansion

Figure 16. **State-Specific Heterogeneity in the Estimated Effect of ACA Medicaid Expansion on Combined Medicaid plus Uninsured Encounters**

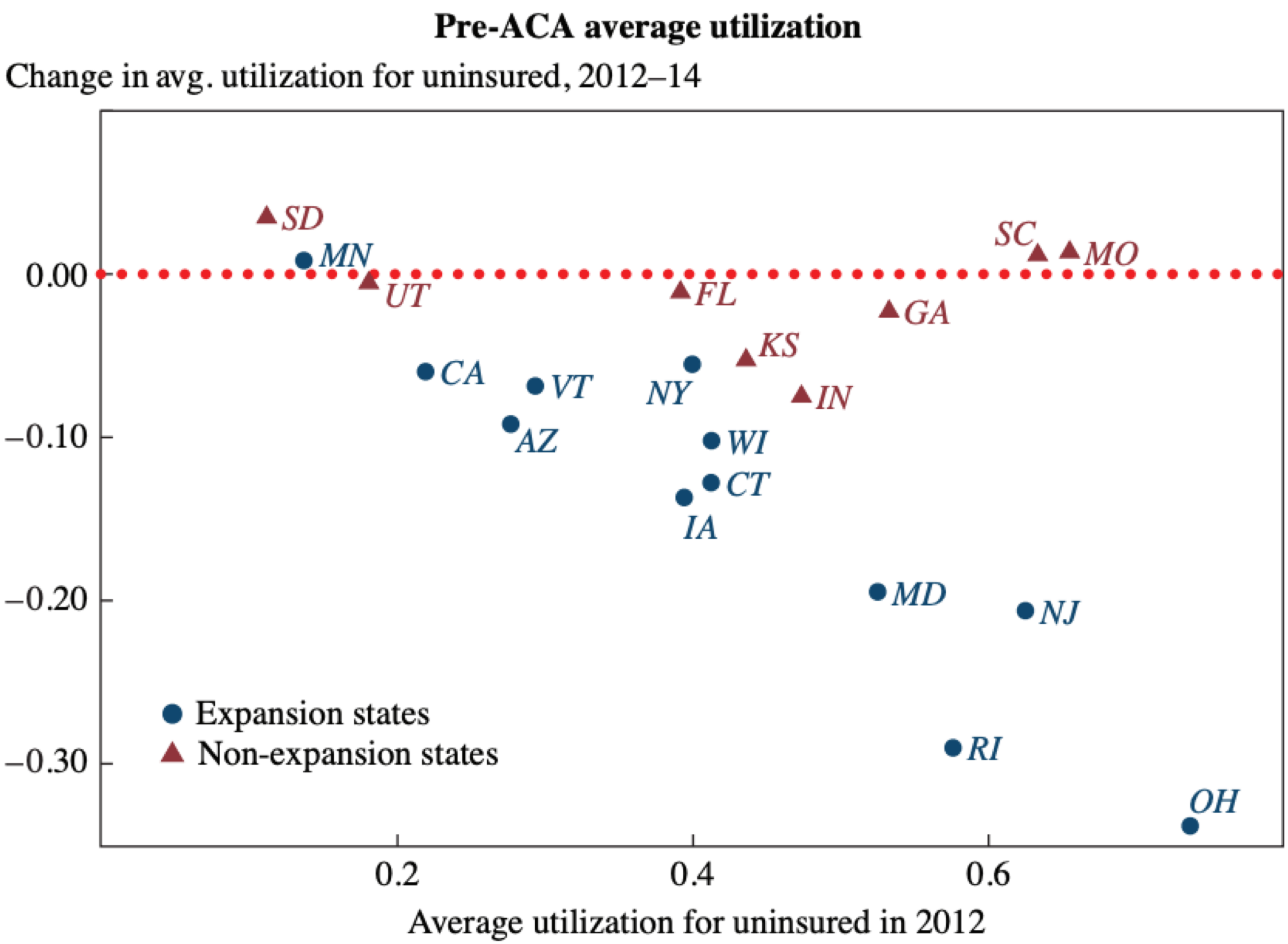


Source: Authors' calculations.

Note: State-specific difference-in-differences estimates of the effect of the ACA Medicaid expansion on total encounters (hospital and emergency department visits) combining Medicaid visits and uninsured visits are shown. The dotted line is the average. State-specific estimates include 95 percent confidence intervals based on standard errors clustered by state and year-month.

Heterogeneity in ACA Medicaid expansion

Figure 19. Exploring State Heterogeneity in Changes in the Average Utilization for Uninsured



Heterogeneity in ACA Medicaid expansion

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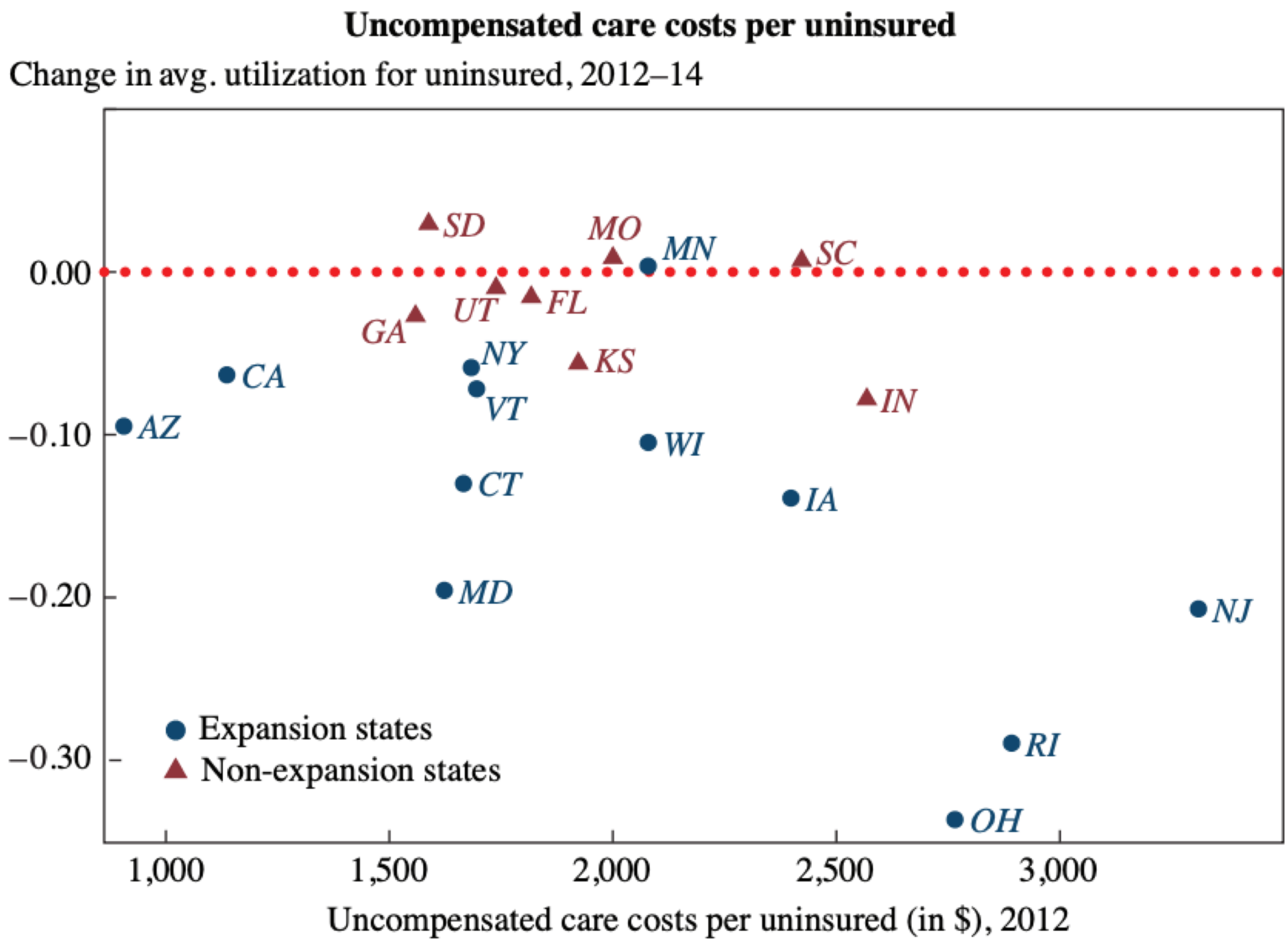

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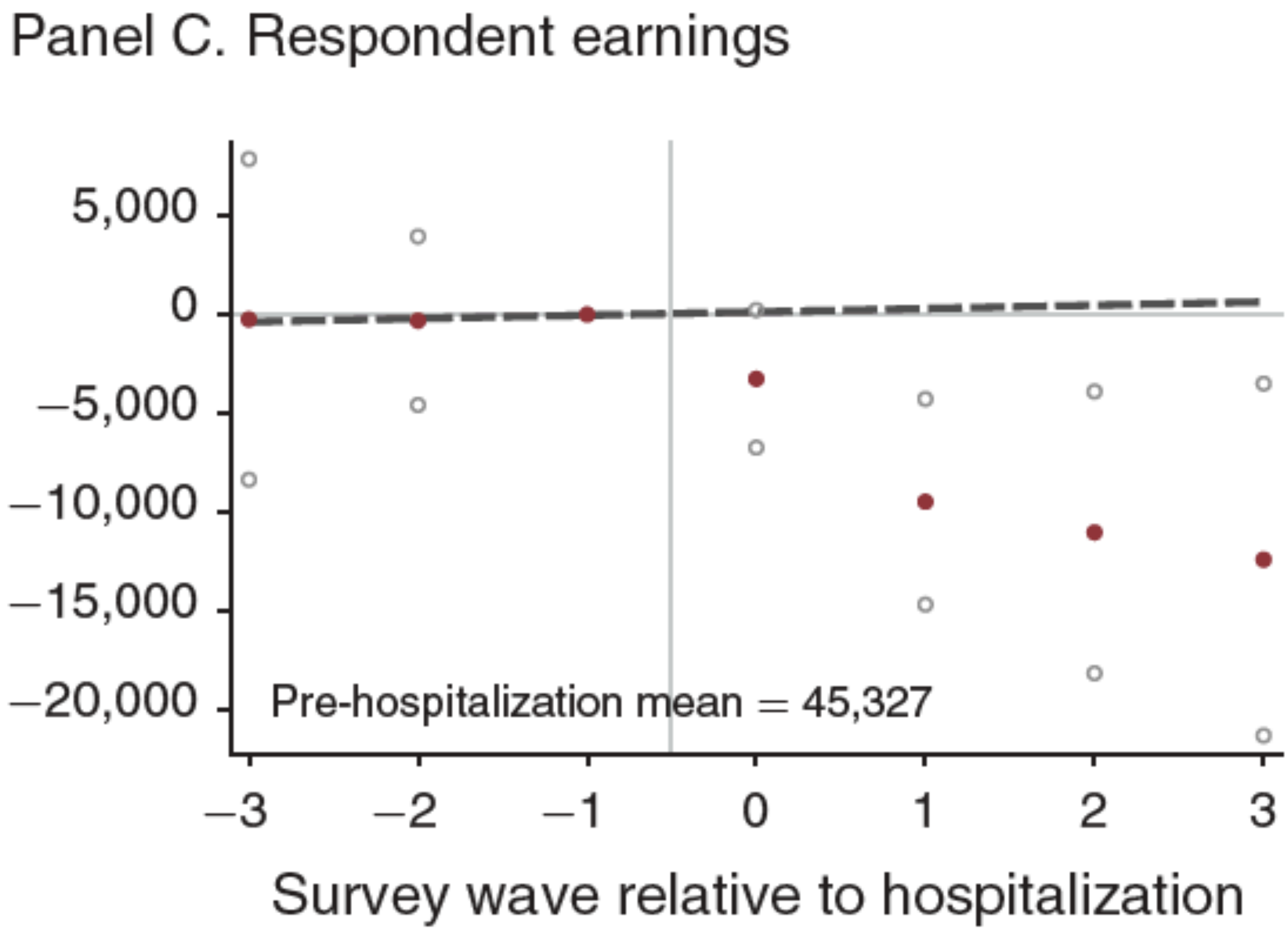
What health insurance does NOT do?

Dobkin et al. AER 2018 study of hospitalizations **[insured sample, age 50-59]**



What health insurance does NOT do?

- Average earnings (of 50-59 year-olds) decline ~19% following a hospitalization
- Similar to average earnings losses from job displacements (e.g., mass layoffs, plant closings)
- Earnings impacts are immediate and persistent (in contrast to out-of-pocket medical spending, which spikes but then quickly declines over time); average annual earnings decline is more than 7 times larger increase in out-of-pocket medical spending
- About 50% of total economic costs (medical expenses + earnings decline) are insured in third year after health shock
- Findings in U.S. contrast w/ Denmark (see Fadlon & Nielsen 2015), where earnings declines are similar in magnitude but mostly insured through **sick pay** & **disability insurance**

Implications: nature of insurance for the "insured"

- The insured still face considerable economic risk from hospital admissions, with the primary source being uninsured earnings (as opposed to out-of-pocket spending)
- 30% of earnings decline are insured (annual total household income declines by about 11%), compared to >90% of medical expenses
- Taking earnings and medical cost impacts together:
  - In 1st year post admission, ~80% of economic consequences are covered
  - By 3rd year post admission, ~60% percent covered
  - Earnings decline is persistent and slightly increasing over time while increase in out-of-pocket medical spending is "front-loaded"
  - Decline in borrowing consistent with large and growing earnings declines

Dobkin et al. *AER* economic model

- Individual lives for two periods, gets utility from consumption and leisure, chooses labor supply in each period, and can save/borrow between periods at r
- Before period 1, health shock with probability p.
  - Generates medical expenses (m) and reduces wages (α_1, α_2)
  - Total size of shock: $m + \alpha_1 w_1 h_1 + \alpha_2 w_2 h_2$
- Health insurance
  - covers λ_m of medical expenses, λ_α of wage decline
  - Define $\lambda_m = \lambda_\alpha = 1$ as "full coverage"
- After health shock realized, individual chooses hours and consumption path subject to budget constraint
  - Can borrow (b), subject to borrowing limit ($L = \gamma Y$)
  - Can have unpaid medical bills (u) at cost of higher $r = r(u,b)$

Dobkin et al. *AER* economic model

Proposition 1: A health shock that is not fully covered generates $\Delta c_1 < 0$, $\Delta c_2 < 0$, $\Delta U < 0$, $\Delta u > 0$

- Signs of Δb, Δr, ΔL, Δy_1 and Δy_2 are all ambiguous but any $\Delta \neq 0$ rejects full coverage.

- Sign of Δb depends on importance of uninsured medical costs $(1 - \lambda_m)m$ compared to the relative income change across periods $(\Delta y_2 - \Delta y_1)$.
  - Increases in out-of-pocket medical expenses increase borrowing, while declines in future income decrease borrowing

- Sign of Δy_1 depends similarly on size of unearned income shock compared to size of income shock

Dobkin et al. *AER* economic model

Proposition 1: A health shock that is not fully covered generates $\Delta c_1 < 0$, $\Delta c_2 < 0$, $\Delta U < 0$, and $\Delta u > 0$; the signs of Δb, Δr, ΔL, Δy_1, and Δy_2 are ambiguous, but $\Delta b \neq 0$ and/or $\Delta r \neq 0$ and/or $\Delta L \neq 0$ and/or $\Delta y_1 \neq 0$ and/or $\Delta y_2 \neq 0$ reject full coverage.

$$\Delta b = \frac{1}{1+(1+r)}\left(\underbrace{(\Delta y_2 - \Delta y_1)}_{\textit{Relative change in income}} + \underbrace{(1-\lambda_m)m}_{\textit{Uninsured medical expenses}} \right)$$

$$sign(\Delta y_1) = sign\left(\underbrace{(-\varepsilon^I)\frac{(1-\lambda_m)m}{1+(1+r)}}_{\textit{Uninsured medical expenses}} - \underbrace{(1+\varepsilon_{h,w})y_1^H((1-\lambda_\alpha)\alpha_1)}_{\textit{Wage change}} \right)$$

Dobkin et al. *AER* economic model

Proposition 1: A health shock that is not fully covered generates $\Delta c_1 < 0$, $\Delta c_2 < 0$, $\Delta U < 0$, and $\Delta u > 0$; the signs of Δb, Δr, ΔL, Δy_1, and Δy_2 are ambiguous, but $\Delta b \neq 0$ and/or $\Delta r \neq 0$ and/or $\Delta L \neq 0$ and/or $\Delta y_1 \neq 0$ and/or $\Delta y_2 \neq 0$ reject full coverage.

$$\Delta b = \frac{1}{1+(1+r)}\Big(\underbrace{(\Delta y_2 - \Delta y_1)}_{\textit{Relative change in income}} + \underbrace{(1-\lambda_m)m}_{\textit{Uninsured medical expenses}} \Big)$$

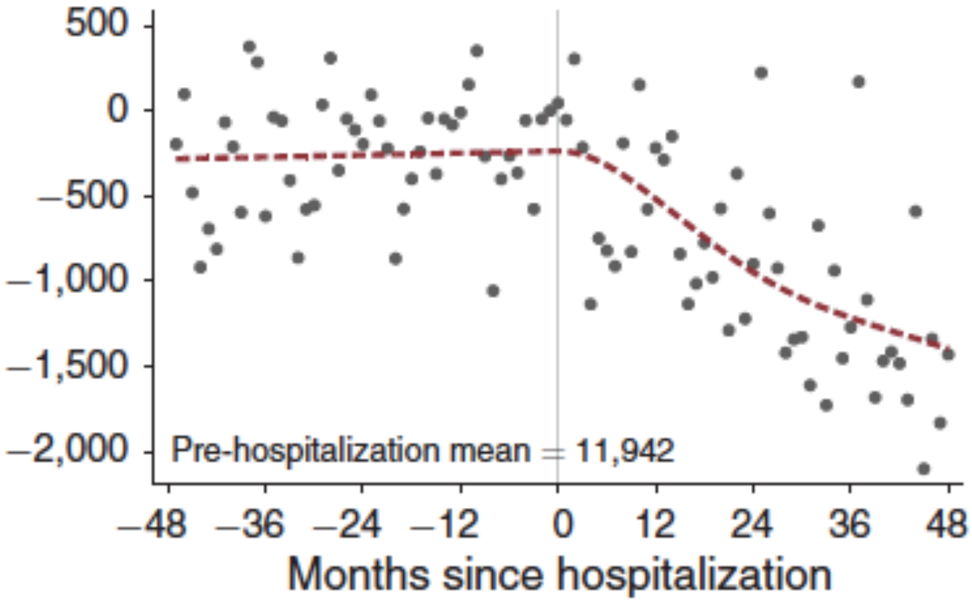
$d(y_1)/dm$

$d\log(h_1)/d\log(w_1)$

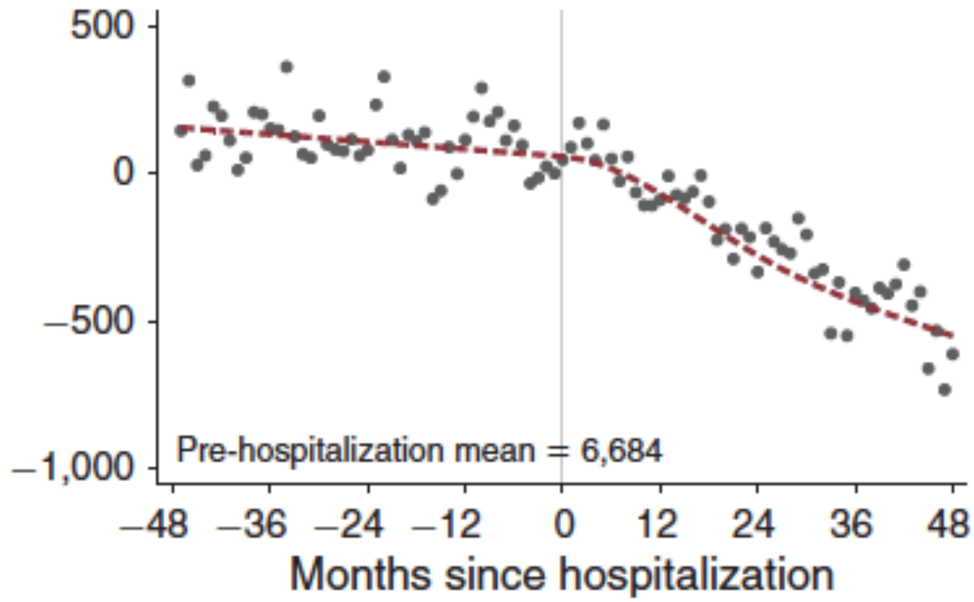
$$sign(\Delta y_1) = sign\left(\underbrace{(-\varepsilon^I)\frac{(1-\lambda_m)m}{1+(1+r)}}_{\textit{Uninsured medical expenses}} - \underbrace{(1+\varepsilon_{h,w})y_1^H((1-\lambda_\alpha)\alpha_1)}_{\textit{Wage change}} \right)$$

Dobkin et al. *AER* economic model

Panel C. Credit card balances



Panel D. Automobile loan balance



$$\Delta b = \frac{1}{1+(1+r)}\Big(\underbrace{(\Delta y_2 - \Delta y_1)}_{\textit{Relative change in income}} + \underbrace{(1-\lambda_m)m}_{\textit{Uninsured medical expenses}} \Big)$$

Dobkin et al. *AER* economic model

Proposition 1: A health shock that is not fully covered generates $\Delta c_1 < 0$, $\Delta c_2 < 0$, $\Delta U < 0$, and $\Delta u > 0$; the signs of Δb, Δr, ΔL, Δy_1, and Δy_2 are ambiguous, but $\Delta b \neq 0$ and/or $\Delta r \neq 0$ and/or $\Delta L \neq 0$ and/or $\Delta y_1 \neq 0$ and/or $\Delta y_2 \neq 0$ reject full coverage.

$$\frac{\Delta U}{g'(c_1)} \approx \frac{\Delta y_1 + \Delta y_2}{1 + \varepsilon_{h,w}} - (1 - \lambda_m)m + \frac{\varepsilon^I}{1 + \varepsilon_{h,w}}(1 - \lambda_m)m$$

Related work on labor market effects of poor health

- "Lifetime costs of bad health" (De Nardi, Paschenko, Porapakkarm 2021 papers.ssrn.com/sol3/papers.cfm?abstract_id=3056885)
  - Structural life-cycle model with shocks to health and medical expenses with endogenous labor supply and savings decisions

  "The monetary lifetime costs of bad health are very concentrated and highly unequally distributed, [and] the largest component of these monetary costs [are] the loss in labor earnings"

- "Impact of Health on Labor Market Outcomes" (Stephens Jr. and Toohey *AEJ-Applied* 2022)
  - Estimates causal effect of health on income using MRFIT RCT covering ~12k men
  - Treatment caused reduced coronary heart disease risk and increased earnings and family income

MRFIT RCT

The Impact of Health on Labor Market Outcomes: Evidence from a Large-Scale Health Experiment

Melvin Stephens Jr.

Desmond Toohey

AMERICAN ECONOMIC JOURNAL: APPLIED ECONOMICS
VOL. 14, NO. 3, JULY 2022
(pp. 367-99)

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Article Information | Comments (0)

Abstract

While economists have posited that health investments increase earnings, isolating the causal effect of health is challenging due to reverse causality and unobserved heterogeneity. We examine the labor market effects of a randomized controlled trial, the Multiple Risk Factor Intervention Trial (MRFIT), which monitored nearly 13,000 men for over six years. We find that this intervention, which provided a bundle of treatments to reduce coronary heart disease mortality, increased earnings and family income. We find few differences in estimated gains by baseline health and occupation characteristics.

Source: https://www.aeaweb.org/articles?id=10.1257/app.20180686

MRFIT RCT

Table 1—Balance of Baseline Characteristics

	SI	UC	Difference
Age	46.43	46.35	0.09
			(0.11)
White	0.898	0.905	−0.007
			(0.005)
High school graduate	0.211	0.208	0.003
			(0.007)
Some college	0.358	0.350	0.008
			(0.009)
College graduate	0.269	0.279	−0.010
			(0.008)
Married	0.887	0.889	−0.002
			(0.006)
Serum cholesterol	254	254	0.22
			(0.65)
Smoker	0.593	0.590	0.004
			(0.009)
Cigarettes/day (with zeroes)	19.2	19.4	−0.13
			(0.36)
Diastolic blood pressure	90.7	90.7	0.02
			(0.16)
CHD mortality risk (percent)	2.09	2.08	−0.016
			(0.027)

Notes: Heteroskedasticity-consistent standard errors for the difference in the means between the SI and UC groups are reported in parentheses. See the text and Neaton et al. (1981) for the calculation of CHD mortality risk. The analysis sample contains 12,562 participants, 6,291 in the SI group and 6,271 in the UC group, who have non-missing data for age, race, education, marital status, and employment status measured at baseline.

MRFIT RCT

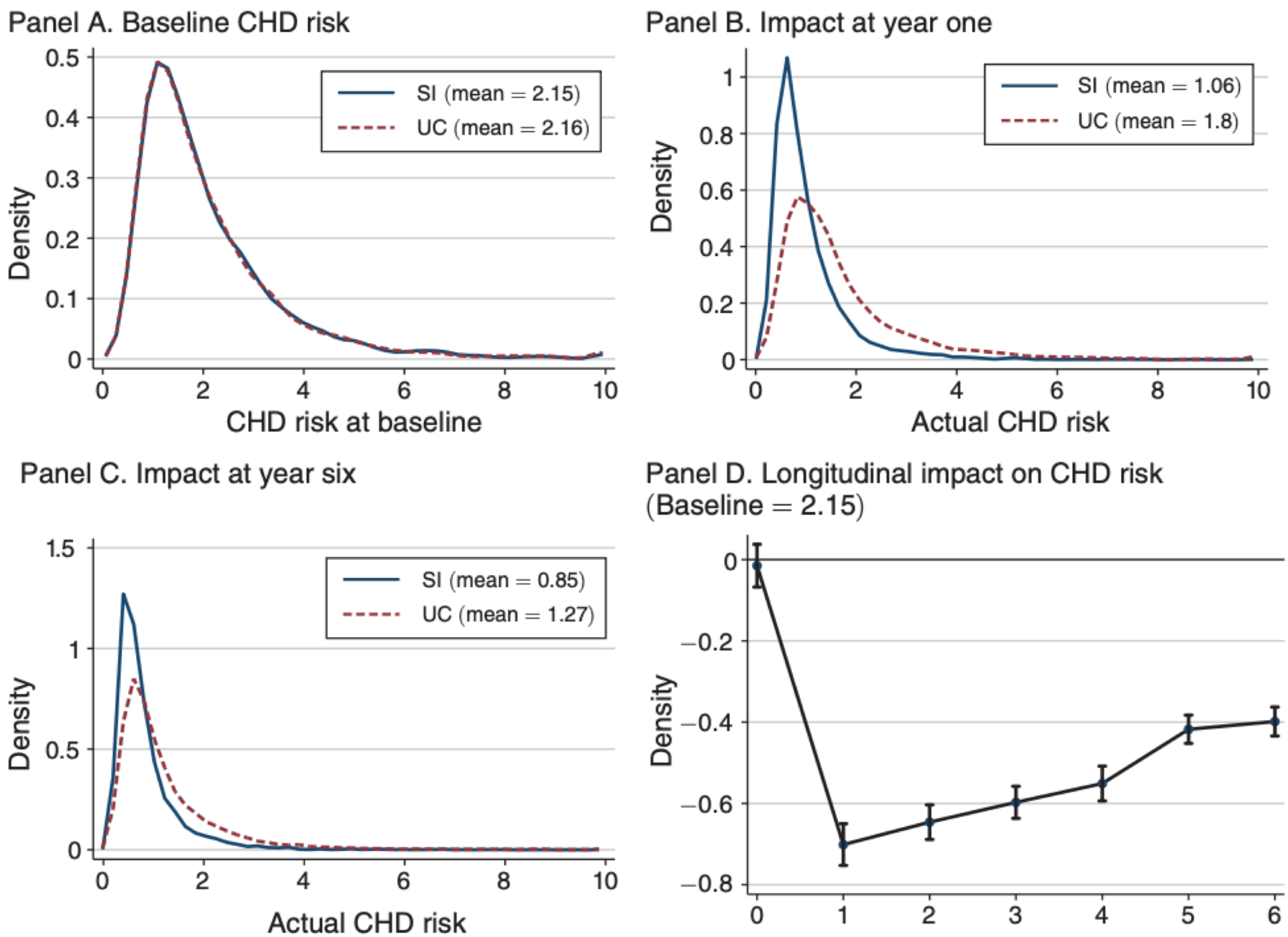


Figure 1. Experimental Impact on CHD Risk

MRFIT RCT

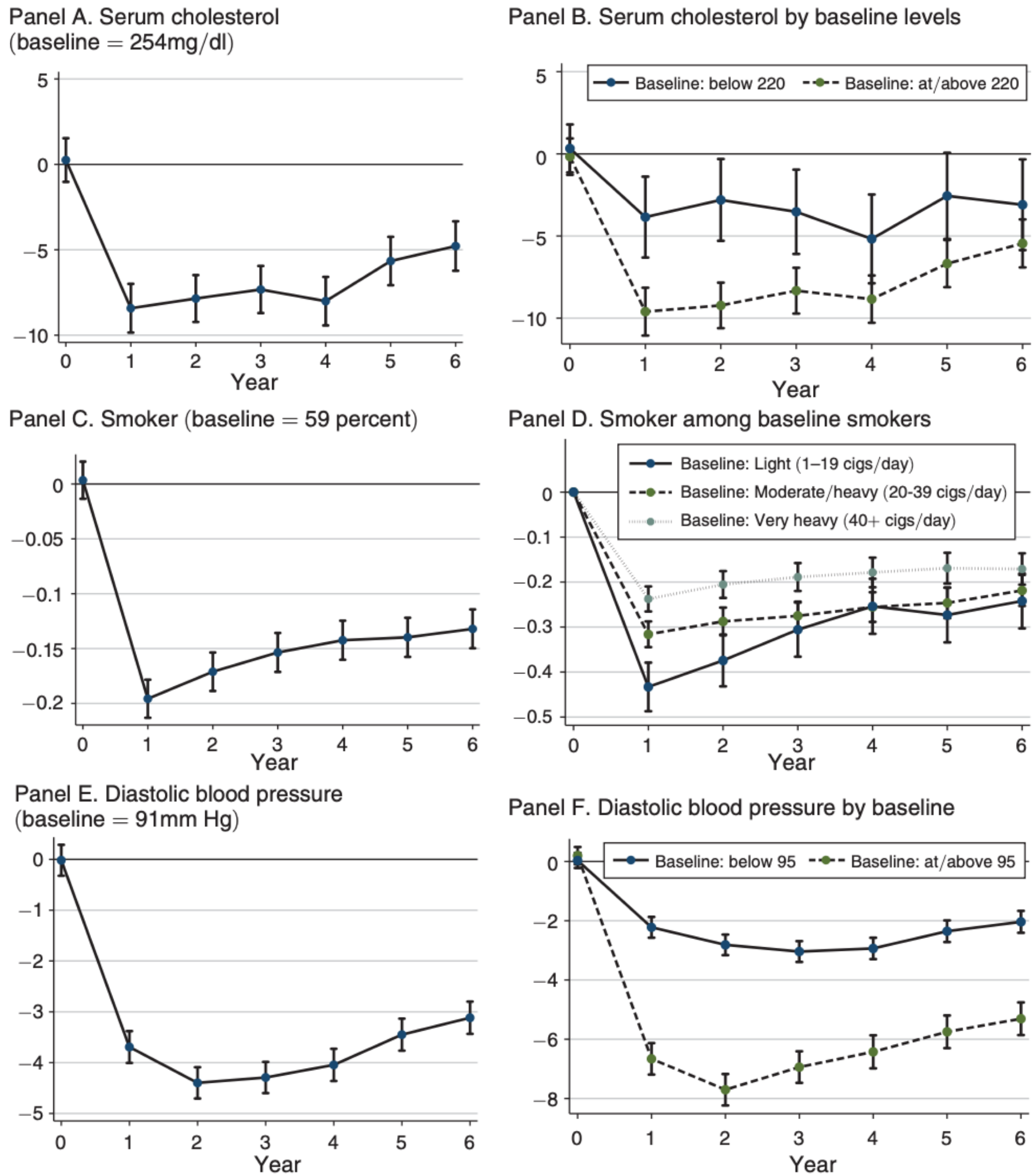
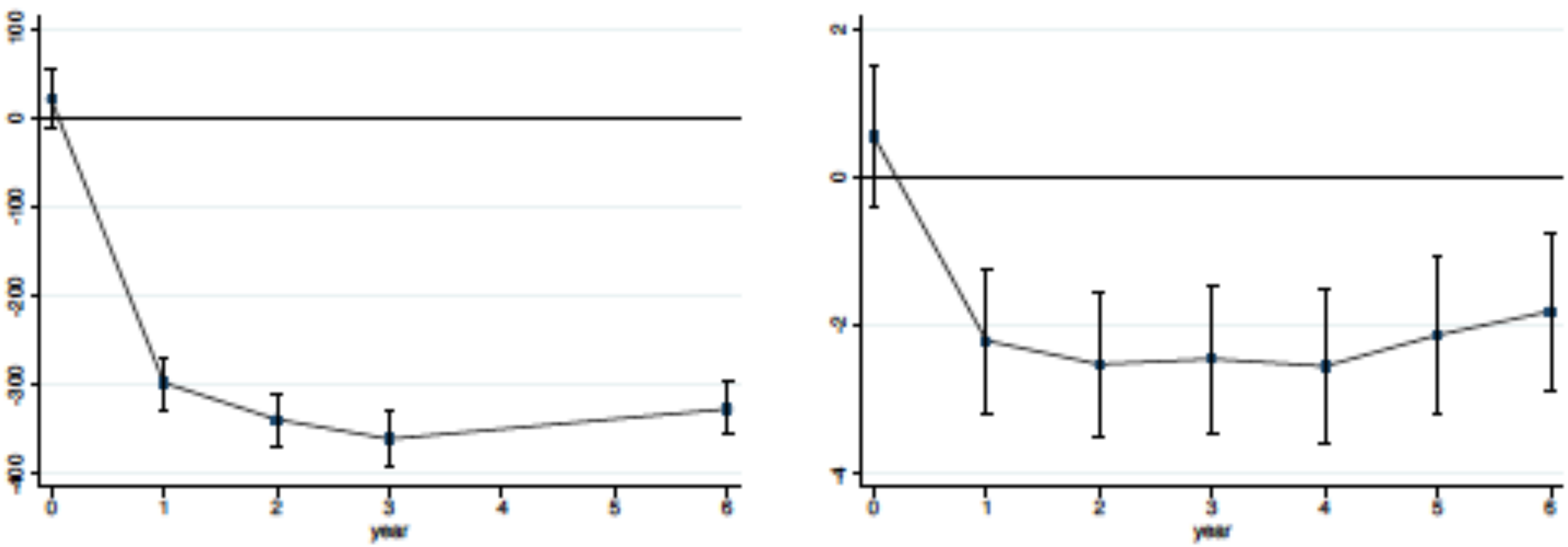


Figure 2. Experimental Impact on Health Outcomes

MRFIT RCT

Figure A.1: Experimental Impact on Additional Cholesterol-Related Outcomes

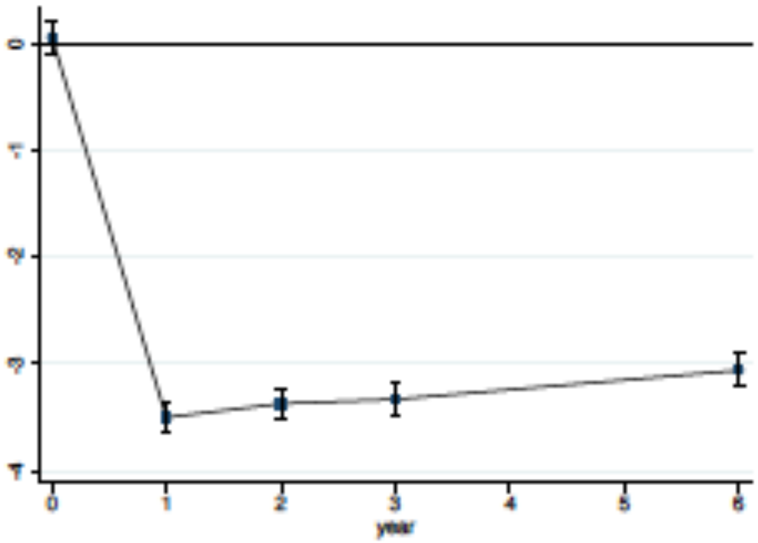


(a) Calories (Baseline=2,369)   (b) Body Weight (Baseline=189 lbs)

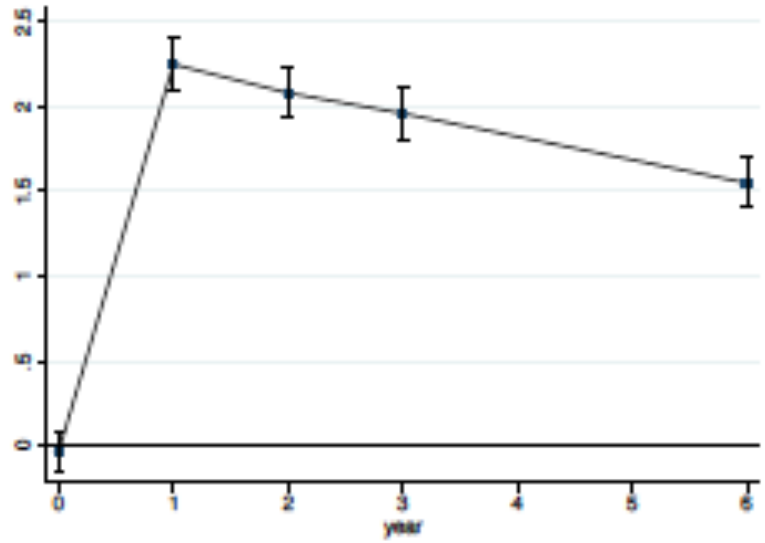
Notes: Each point is coefficient from a different regression of the form of equation (1). The 95% confidence interval bars are generated using heteroskedastic-consistent variances. The regression controls are baseline measures and include a full set of indicators for age, an indicator for being white, indicators for four education groups, and a marital status indicator. The sample is initially restricted to the 12,562 MRFIT respondents with nonmissing age, education, marital status, race, and employment status at baseline. Estimates for each year further restrict to observations with nonmissing outcomes and controls for that year.

MRFIT RCT

Figure A.1: Experimental Impact on Additional Cholesterol-Related Outcomes



(c) Saturated Fat (Baseline=13.7%)

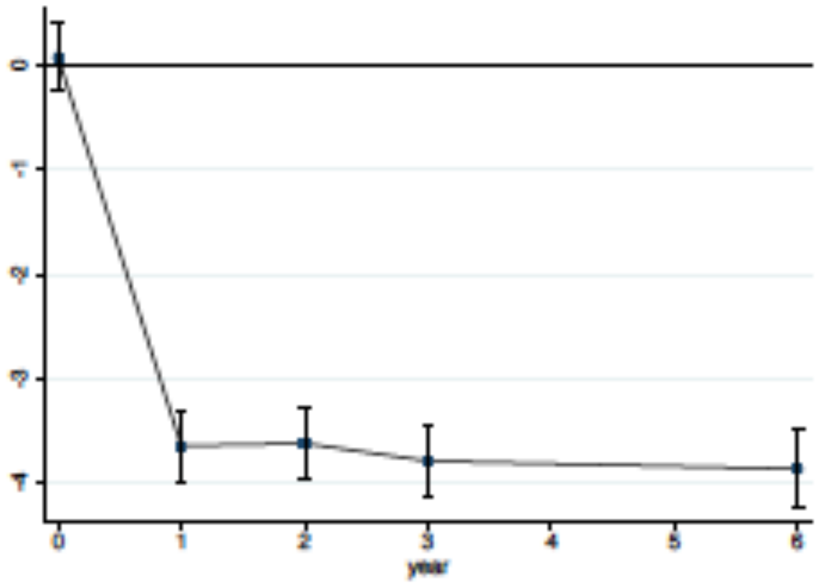


(d) Unaturated Fat (Baseline=6.3%)

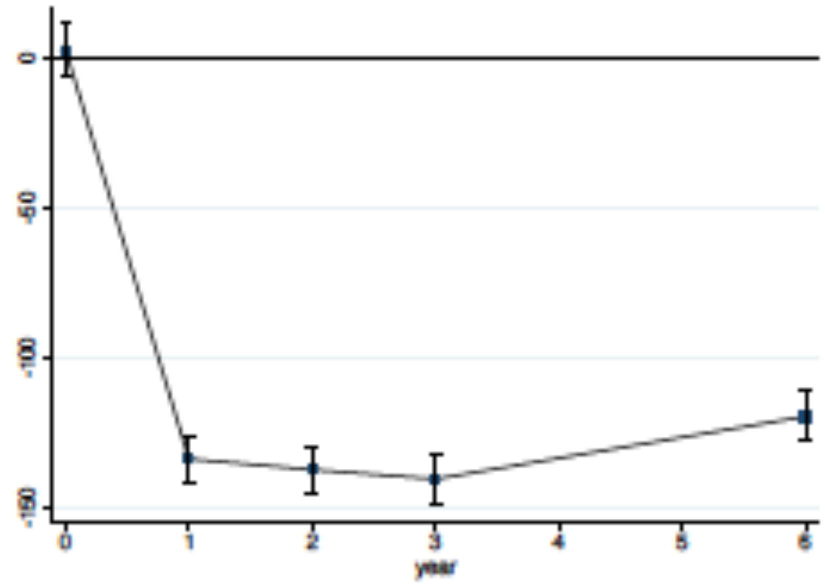
Notes: Each point is coefficient from a different regression of the form of equation (1). The 95% confidence interval bars are generated using heteroskedastic-consistent variances. The regression controls are baseline measures and include a full set of indicators for age, an indicator for being white, indicators for four education groups, and a marital status indicator. The sample is initially restricted to the 12,562 MRFIT respondents with nonmissing age, education, marital status, race, and employment status at baseline. Estimates for each year further restrict to observations with nonmissing outcomes and controls for that year.

MRFIT RCT

Figure A.1: Experimental Impact on Additional Cholesterol-Related Outcomes



(e) Dietary Cholesterol (Baseline=384 mg/dl)

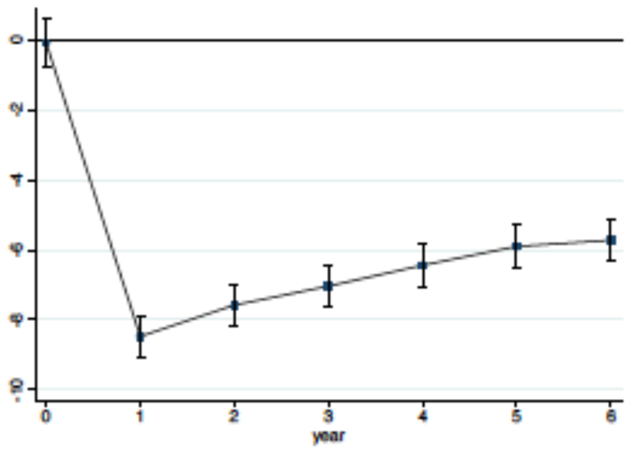


(f) Total Fat (Baseline=37.8%)

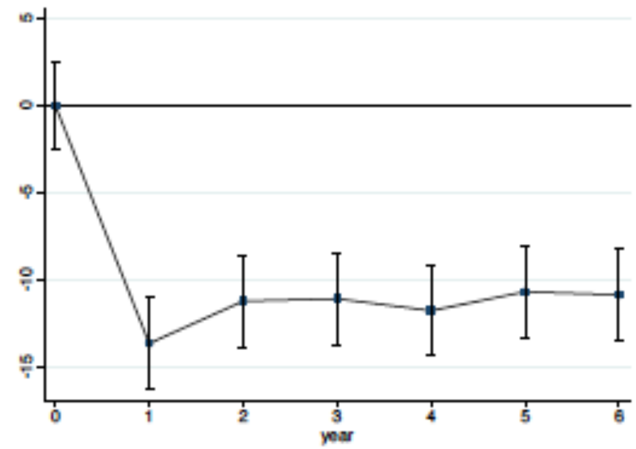
Notes: Each point is coefficient from a different regression of the form of equation (1). The 95% confidence interval bars are generated using heteroskedastic-consistent variances. The regression controls are baseline measures and include a full set of indicators for age, an indicator for being white, indicators for four education groups, and a marital status indicator. The sample is initially restricted to the 12,562 MRFIT respondents with nonmissing age, education, marital status, race, and employment status at baseline. Estimates for each year further restrict to observations with nonmissing outcomes and controls for that year.

MRFIT RCT

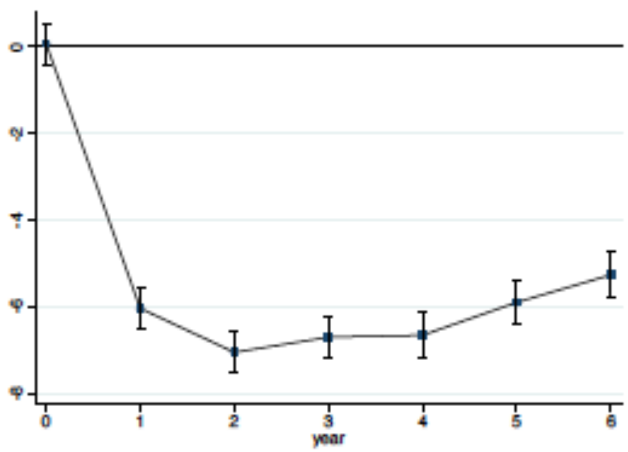
Figure A.2: Experimental Impact on Additional Health Outcomes



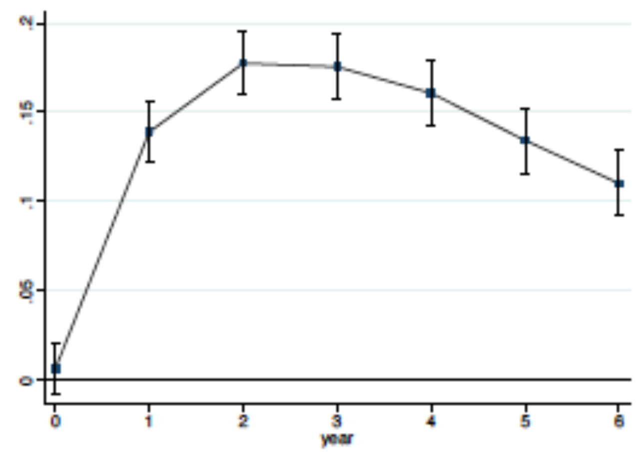
(a) Cigarettes/Day (Baseline=19)



(b) Serum Thiocyanate (Baseline=131)



(c) Systolic Blood Pressure
(Baseline=135 mm Hg)



(d) Taking Blood Pressure Medication
(Baseline=19.3%)

Notes: Each point is coefficient from a different regression of the form of equation (1). The 95% confidence interval bars are generated using heteroskedastic-consistent variances. The regression controls are baseline measures and include a full set of indicators for age, an indicator for being white, indicators for four education groups, and a marital status indicator. The sample is initially restricted to the 12,562 MRFIT respondents with nonmissing age, education, marital status, race, and employment status at baseline. Estimates for each year further restrict to observations with nonmissing outcomes and controls for that year.

MRFIT RCT

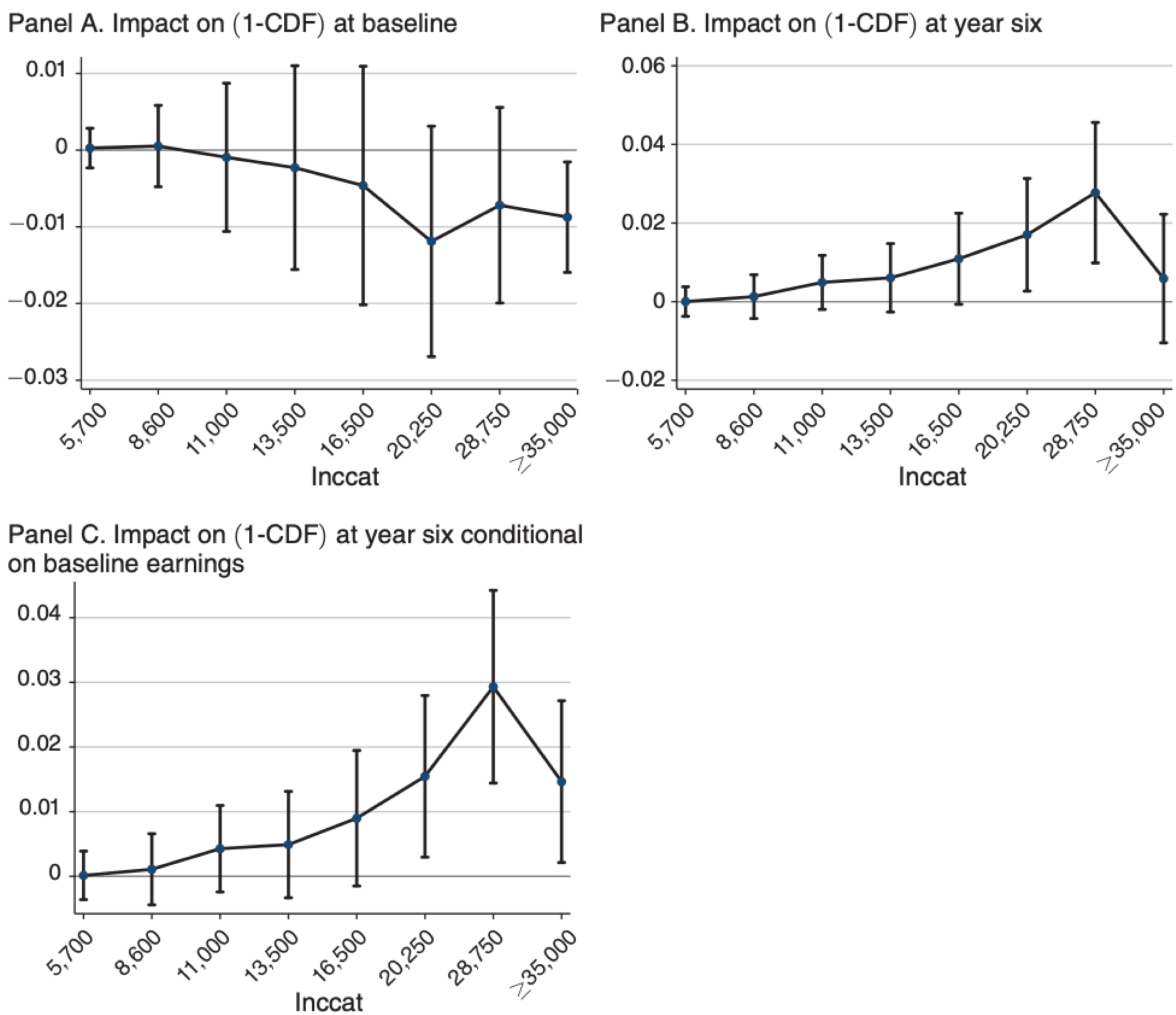


FIGURE 3. EXPERIMENTAL IMPACT ON EARNINGS

MRFIT RCT

TABLE 3—EARNINGS AND FAMILY INCOME REGRESSIONS

	Baseline		Year six			Year six Age ≤ 48
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Earnings						
SI	−0.015	−0.010	0.020	0.027	0.028	0.023
	(0.008)	(0.006)	(0.011)	(0.009)	(0.008)	(0.009)
Observations	12,326	12,321	9,508	9,215	9,212	5,982
Panel B. Family income						
SI	−0.013	−0.009	0.035	0.038	0.040	0.030
	(0.008)	(0.007)	(0.012)	(0.009)	(0.009)	(0.011)
Observations	12,399	12,395	10,845	10,524	10,521	6,425
Additional controls:						
Baseline health and demographics		X			X	X
Baseline outcome				X	X	X

Notes: Heteroskedasticity-consistent standard errors are reported in parentheses. This table reports interval regression estimates in which the cutpoints are known and the unobserved latent outcome is assumed to be log normally distributed. The baseline health and demographic controls are serum cholesterol, diastolic blood pressure, number of cigarettes smoked, an indicator for being a smoker, a full set of indicators for age, an indicator for being white, indicators for four education groups, and a marital status indicator. The baseline outcome controls used for the year six outcomes in columns 4–6 are a set of indicators for the corresponding outcome at baseline. The earnings regressions are restricted to those who are employed for the relevant survey waves. Column 6 further restricts to participants who were 48 or younger at baseline. The outcomes are nine-group categorical earnings and income measures with cut points at \$4,200, \$7,200, \$10,000, \$12,000, \$15,000, \$18,000, \$22,500, and \$35,000.

Class #1 Outline

- Brief background on health insurance in the U.S.
- Brief review of the economics of uncertainty and the demand for insurance
- Review of research on the effects of health insurance on out-of-pocket medical spending, medical debt, and consumer bankruptcy
- **Discussion of what health insurance does NOT do**
- Why are people (still) uninsured?
- Conclusions and open questions

Class #1 Outline

- Brief background on health insurance in the U.S.
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- **Why are people (still) uninsured?**
- Conclusions and open questions

Why are people (still) uninsured?

- Textbook rationale for health insurance is **protection against financial risk**

- But health insurance also likely improves health outcomes, at least for some consumers, including reductions in mortality (see, e.g., Goldin, Lurie, McCubbin *QJE* 2021 https://academic.oup.com/qje/article/136/1/1/5911132)

TheUpshot

The I.R.S. Sent a Letter to 3.9 Million People. It Saved Some of Their Lives.

- Puzzle: If health insurance provides financial protection and reduces mortality, **why do people in the U.S. remain uninsured?**

Demand/WTP for Medicaid and/or subsidized insurance

- Medicaid is an in-kind transfer that may be valued at more or less than cost. Government (e.g., CBO) typically assumes that Medicaid is valued at average cost (by recipients).
  - Argument for "more" -- typical model of demand for insurance implies that demand is expected cost + risk premium (and RP > 0 when consumers are risk-averse)
  - Argument for "less" -- uncompensated care and/or implicit insurance substituting for formal insurance could reduce WTP below expected cost
- Several recent papers make progress estimating WTP for Medicaid and subsidized insurance, and all of the papers find very low WTP for health insurance -- i.e., WTP < E[cost], but WTP is "supposed to be" E[cost] + RP, with RP > 0

Subsidizing Health Insurance for Low-Income Adults: Evidence from Massachusetts

Amy Finkelstein
Nathaniel Hendren
Mark Shepard

AMERICAN ECONOMIC REVIEW
VOL. 109, NO. 4, APRIL 2019
(pp. 1530-67)

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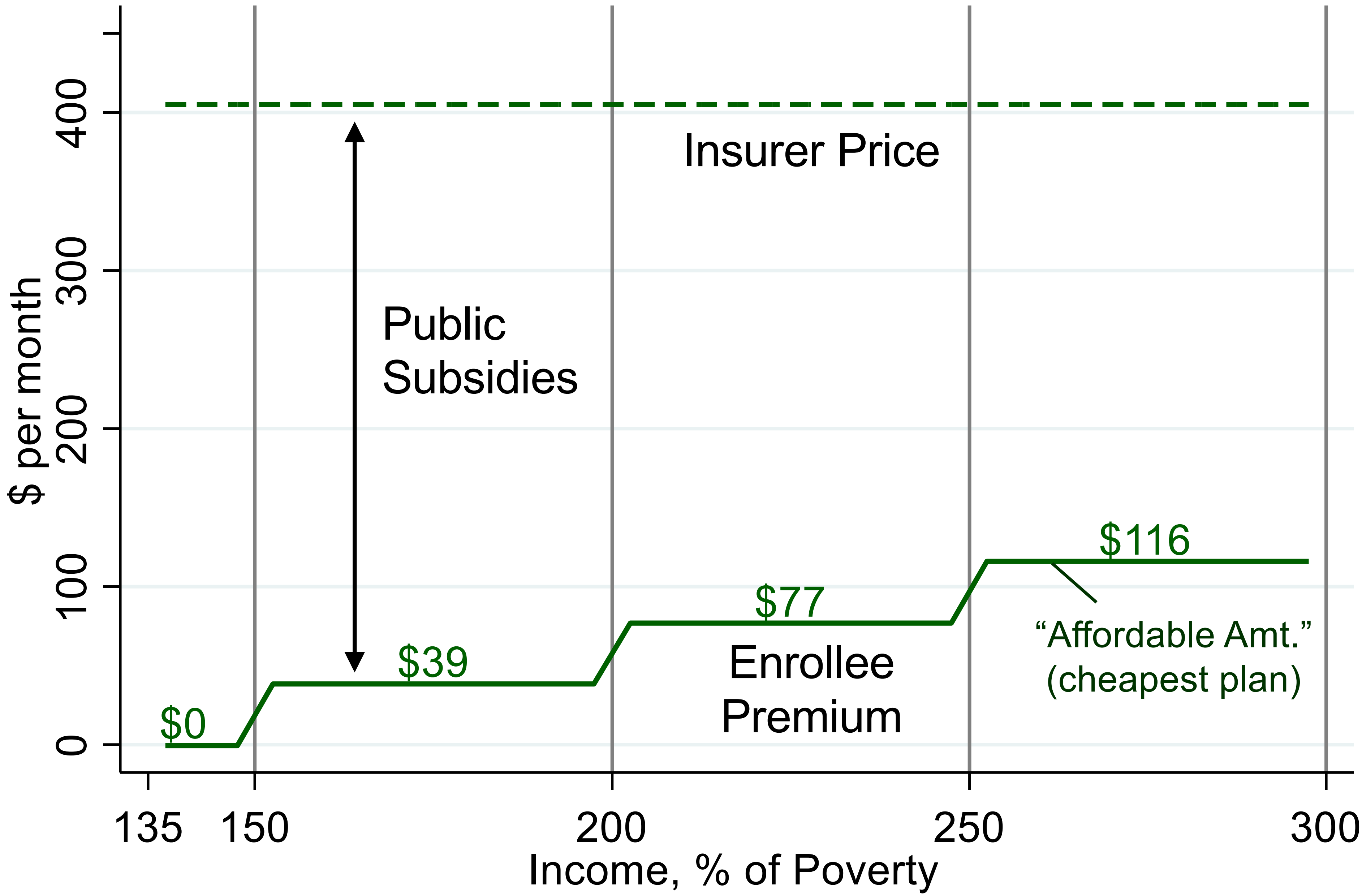
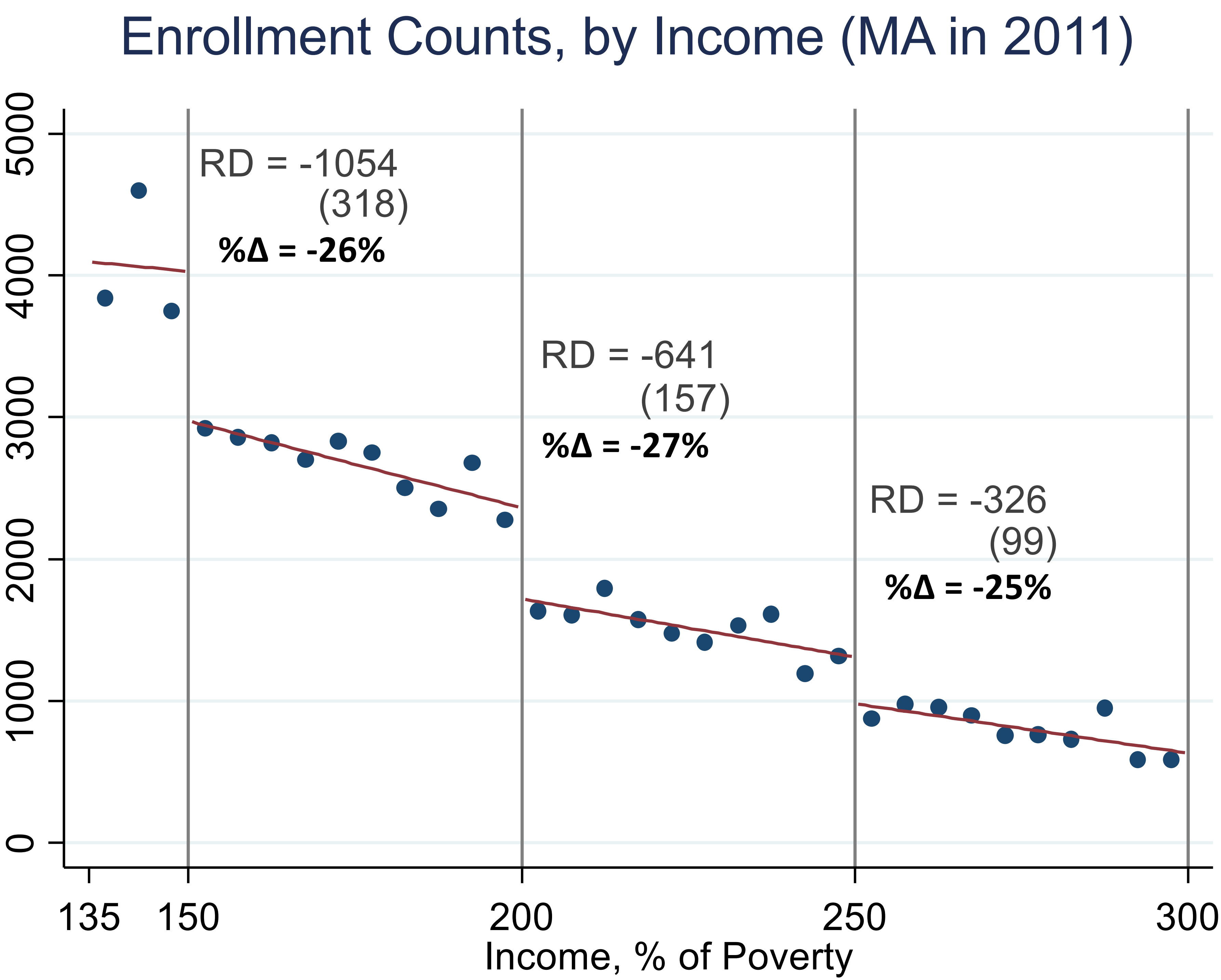
Article Information

Abstract

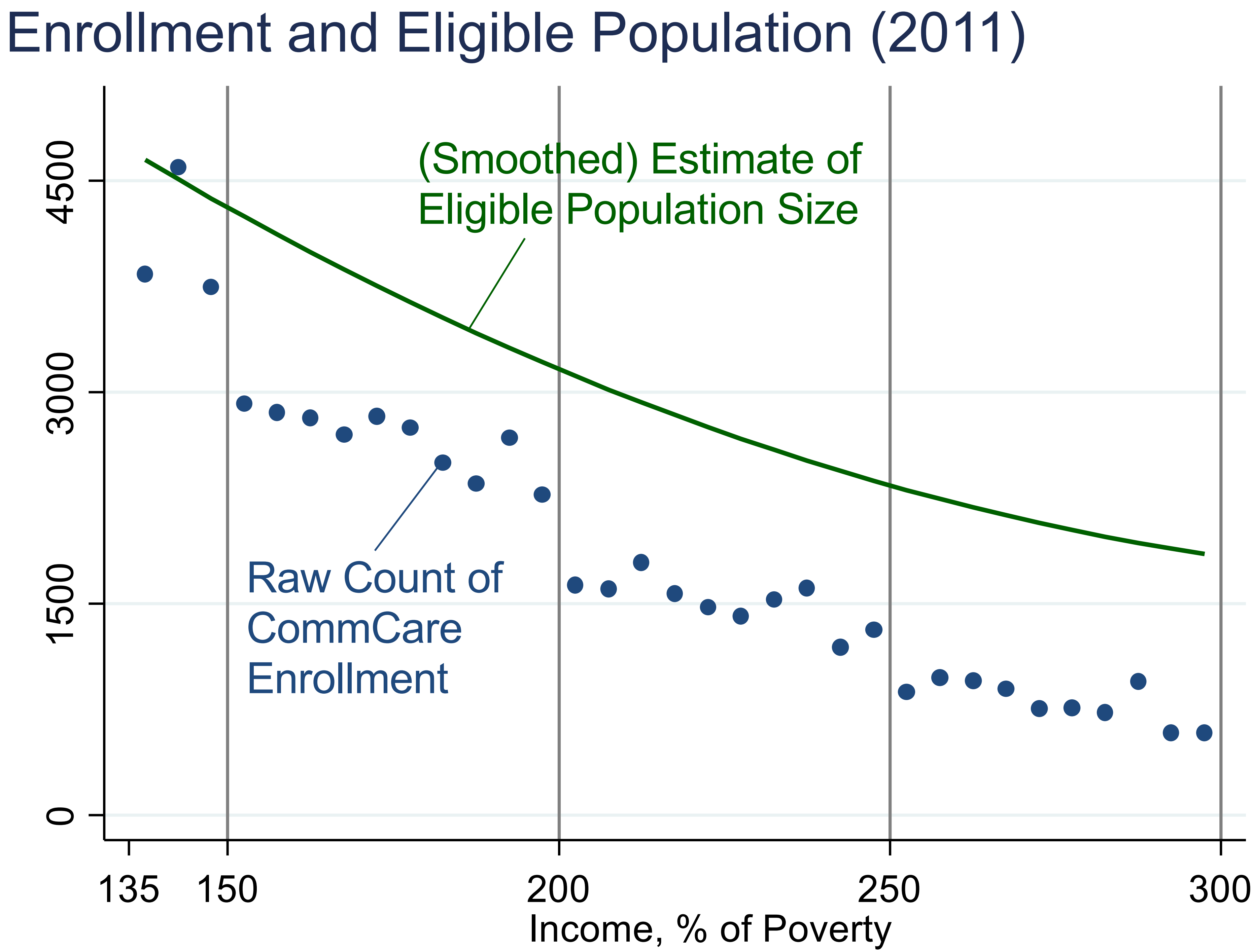
How much are low-income individuals willing to pay for health insurance, and what are the implications for insurance markets? Using administrative data from Massachusetts' subsidized insurance exchange, we exploit discontinuities in the subsidy schedule to estimate willingness to pay and costs of insurance among low-income adults. As subsidies decline, insurance take-up falls rapidly, dropping about 25 percent for each $40 increase in monthly enrollee premiums. Marginal enrollees tend to be lower-cost, indicating adverse selection into insurance. But across the entire distribution we can observe (approximately the bottom 70 percent of the willingness to pay distribution) enrollees' willingness to pay is always less than half of their own expected costs that they impose on the insurer. As a result, we estimate that take-up will be highly incomplete even with generous subsidies. If enrollee premiums were 25 percent of insurers' average costs, at most half of potential enrollees would buy insurance; even premiums subsidized to 10 percent of average costs would still leave at least 20 percent uninsured. We briefly consider potential explanations for these findings and their normative implications.

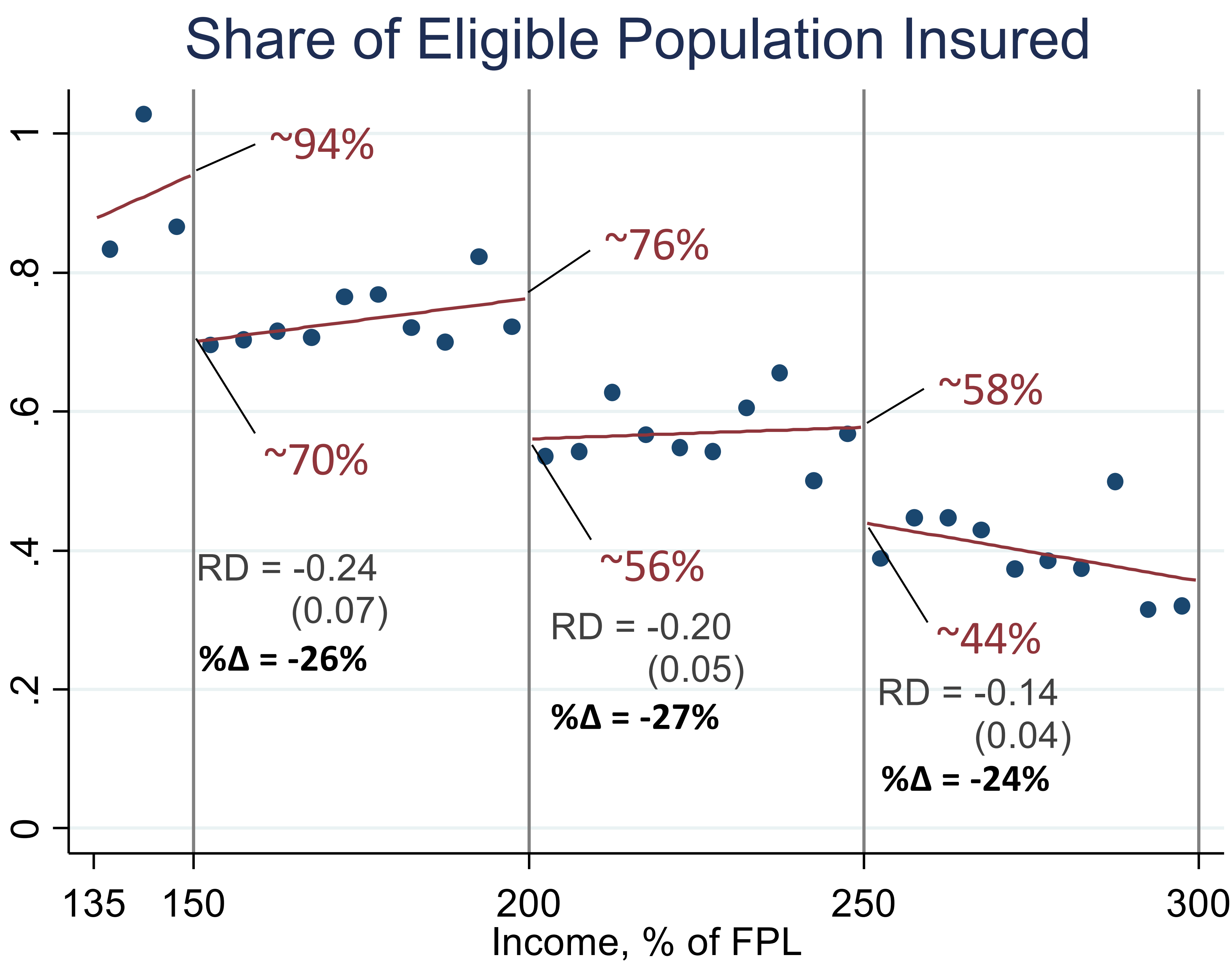
Finkelstein-Hendren-Shepard *AER*

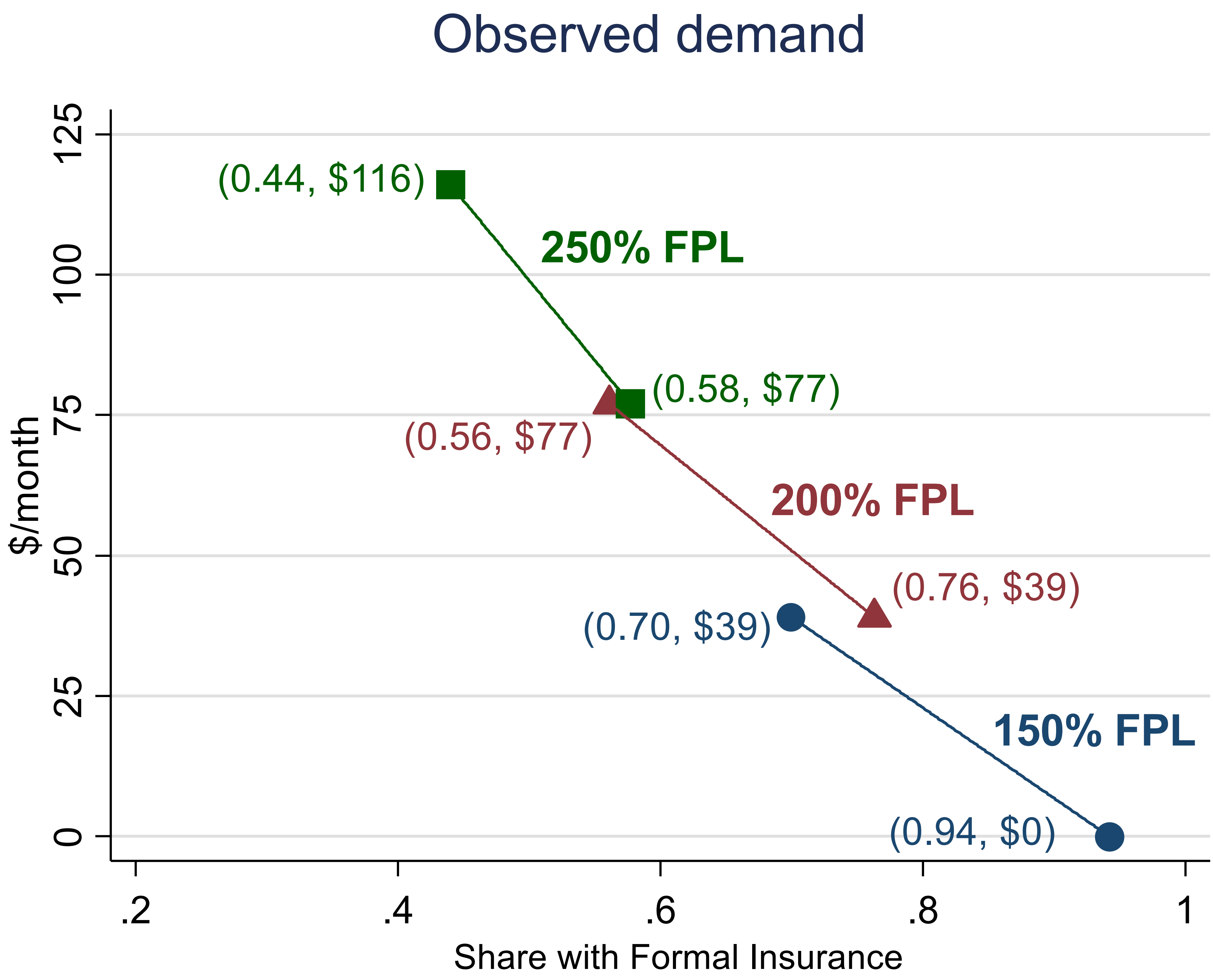


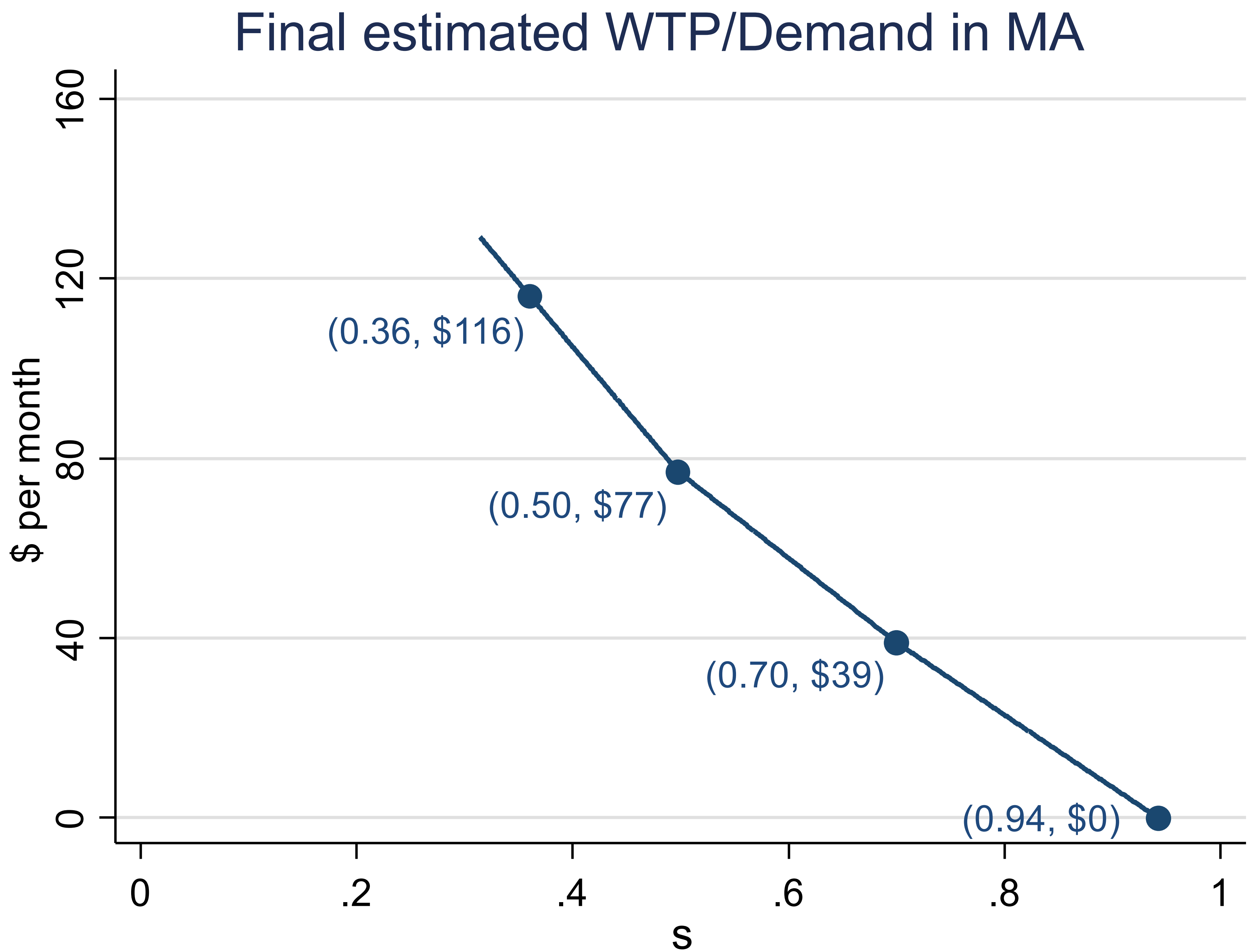


Enrollment Counts, by Income (MA in 2011)
RD = -1054
(318)
%Δ = -26%
RD = -641
(157)
%Δ = -27%
RD = -326
(99)
%Δ = -25%
0
1000
2000
3000
4000
5000
135
150
200
250
300
Income, % of Poverty


Enrollment and Eligible Population (2011)
(Smoothed) Estimate of
Eligible Population Size
Raw Count of
CommCare
Enrollment
4500
3000
1500
0
135
150
200
250
300
Income, % of Poverty

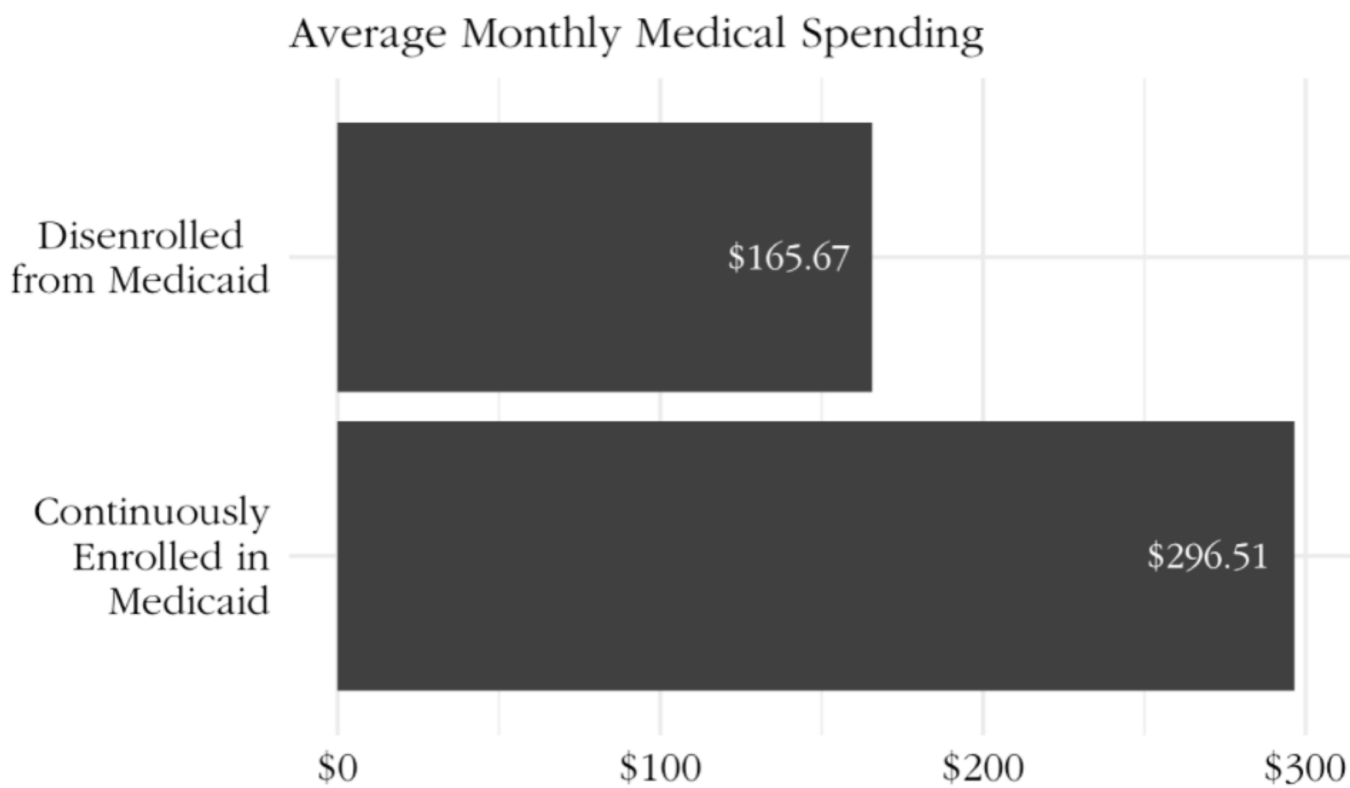

Share of Eligible Population Insured
0
.2
.4
.6
.8
1
135
150
200
250
300
Income, % of FPL
~94%
~70%
~76%
~56%
~58%
~44%
RD = -0.24
(0.07)
%Δ = -26%
RD = -0.20
(0.05)
%Δ = -27%
RD = -0.14
(0.04)
%Δ = -24%


Observed demand
(0.44, $116)
250% FPL
(0.58, $77)
(0.56, $77)
200% FPL
(0.76, $39)
(0.70, $39)
150% FPL
(0.94, $0)
$/month
0
25
50
75
100
125
.2
.4
.6
.8
1
Share with Formal Insurance


Final estimated WTP/Demand in MA
$ per month
160
120
80
40
0
(0.36, $116)
(0.50, $77)
(0.70, $39)
(0.94, $0)
0
.2
.4
.6
.8
1
s

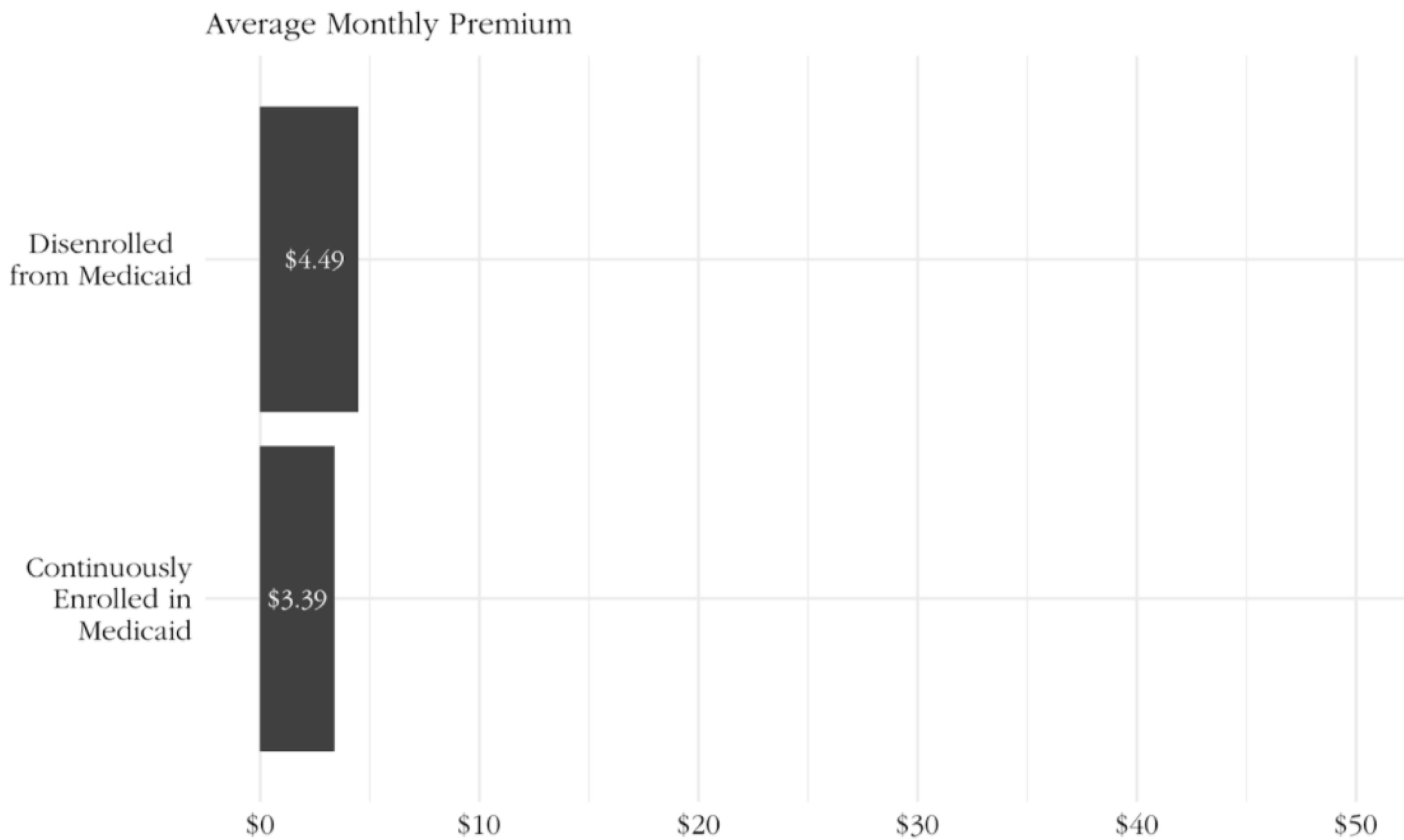
Low demand/WTP for insurance – Additional evidence

Additional evidence in MI:



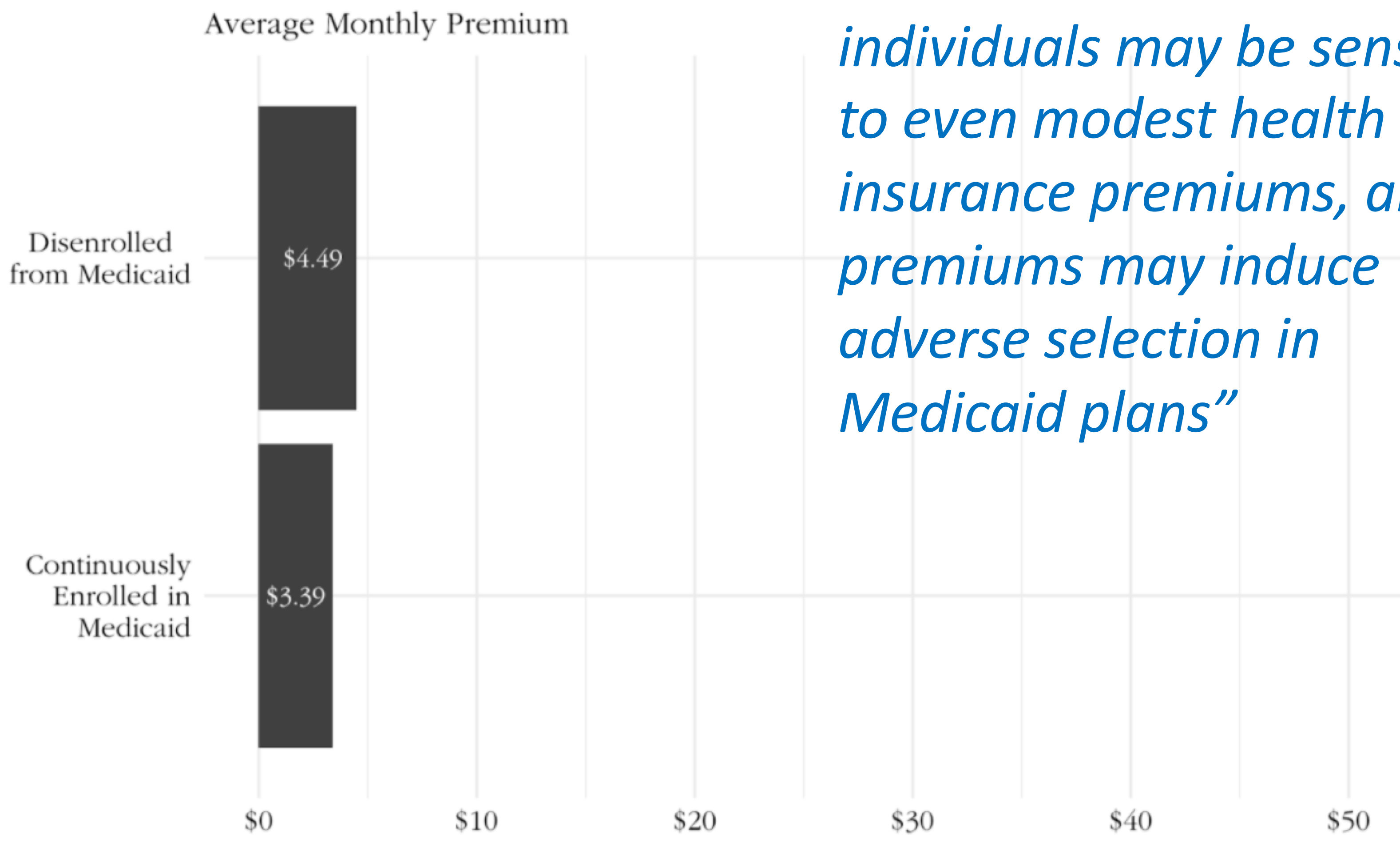
Low demand/WTP for insurance – Additional evidence

Additional evidence in MI:



Low demand/WTP for insurance – Additional evidence

Additional evidence in MI:



Cliff et al. conclude:
"Healthier low-income individuals may be sensitive to even modest health insurance premiums, and premiums may induce adverse selection in Medicaid plans"

The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment

Amy Finkelstein

Massachusetts Institute of Technology

Nathaniel Hendren

Harvard University

Erzo F. P. Luttmer

Dartmouth College

We develop frameworks for welfare analysis of Medicaid and apply them to the Oregon Health Insurance Experiment. Across different approaches, we estimate low-income uninsured adults' willingness to pay for Medicaid between \$0.5 and \$1.2 per dollar of the resource cost of providing Medicaid; estimates of the expected transfer Medicaid provides to recipients are relatively stable across approaches, but estimates of its additional value from risk protection are more variable. We also estimate that the resource cost of providing Medicaid to an additional recipient is only 40 percent of Medicaid's total cost; 60 percent of Medicaid spending is a transfer to providers of uncompensated care for the low-income uninsured.

Finkelstein et al. *JPE* conclusions

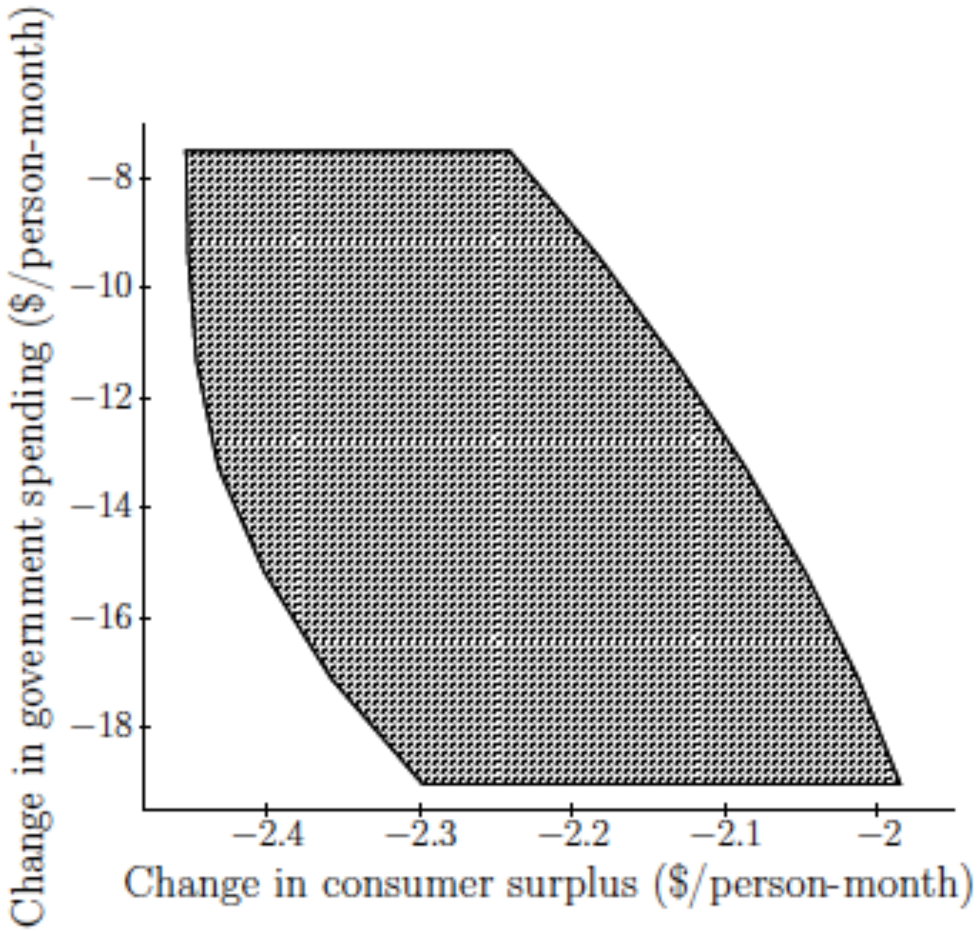
“An uninsured person would choose the status quo over giving up ‘G’ in consumption to obtain Medicaid [where ‘G’ equals gross cost of Medicaid]. This contrasts with the current approach used by the CBO to value Medicaid at government cost”

“Whether Medicaid’s Marginal Value of Public Funds (MVPF) compares favorably to the EITC depends critically on the ultimate economic incidence of the transfers to external parties”

“Medicaid is best conceived of as having two distinct parts: a subsidized health insurance product for low-income individuals and a transfer to external parties who would otherwise subsidize medical care for the low-income uninsured. We estimate that $0.60 of every $1 of government Medicaid spending is a transfer to these external parties. This suggests the importance of future work studying their immediate and ultimate economic incidence.”

Tebaldi et al. *Econometrica*

"Our findings suggest that consumers value health insurance significantly less than it would cost in premium subsidies to induce them to purchase a plan"



***(b)** The joint identified set of consumer surplus and government spending.*

Tebaldi et al. *Econometrica*

"Our findings suggest that consumers value health insurance significantly less than it would cost in premium subsidies to induce them to purchase a plan"

Table 4: The Impacts of Reducing Premium Subsidies by $10 per Month

	140 - 400% FPL Change in consumer surplus		140 - 250% FPL Change in consumer surplus		250 - 400% FPL Change in consumer surplus		140 - 400% FPL Associated change in subsidy outlays	
	LB	UB	LB	UB	LB	UB	LB	UB
Average ($/person-month)	-2.45	-1.99	-3.16	-2.55	-1.55	-1.27	-19.03	-7.50
Aggregate ($ million/year)	-77.82	-62.99	-57.59	-46.48	-22.48	-18.33	-603.89	-237.80

Tebaldi et al. *Econometrica*

Tebaldi et al. conclude: *“A $10 decrease in monthly premium subsidies would cause a decline of 1.8%-6.7% in the proportion of subsidized adults with coverage. The reduction in consumer surplus would be $63-$74 million, while the savings in yearly subsidy outlays would be $209-$601 million”*

…

“These results are consistent with a growing number of empirical papers showing that consumers value individual health insurance significantly less than it costs in subsidies to induce them to purchase a plan”

Why is WTP for Health Insurance Below Own Costs?

- **Behavioral biases** (inattention, inertia, information, misperception…)
  - Very difficult to rule out completely
  - Finkelstein et al. *AER* argue against inattention/inertia by zooming in on demand for new enrollees

- **Moral hazard** – standard textbook explanation for WTP < Cost
  - But required magnitude not plausible
  - Moral hazard would have to increase costs by ~200% to explain gap between WTP and Costs in Finkelstein et al. *AER*
  - Oregon experiment moral hazard estimate: 25%

- **Uncompensated care** (charity care, unpaid bills)
  - Quantitatively important: Low-income uninsured pay ~20% of their medical costs out of pocket (Mahoney AER; Finkelstein et al. *JPE*)
  - More in Class #4!

Low Demand/WTP for ~~health~~ **flood** insurance

Adaptation and Adverse Selection in Markets for Natural Disaster Insurance

Katherine R. H. Wagner

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Abstract

This paper quantifies frictions in uptake, tests for adverse selection, and analyzes welfare effects of proposed reforms in natural disaster insurance markets. I find that willingness to pay is remarkably low. In high-risk flood zones, fewer than 60 percent of homeowners purchase flood insurance even though premiums are only two-thirds of own costs. Estimating flood insurance demand and cost elasticities using house-level variation in premiums from recent US congressional reforms reveals that these homeowners select into insurance based on observable differences in adaptation but not private information about risk. These findings change the sign of predicted welfare effects of proposed policies.

Low Demand/WTP for ~~health~~ **flood** insurance

Wagner (2021) tests for adverse selection in flood insurance, and she finds limited evidence of selection based on private information. More surprisingly, she finds:

"WTP is remarkably low. In high-risk flood zones, fewer than 60% of homeowners purchase flood insurance even though insurance premia are only about two-thirds of own costs"

"Only about half of high-risk homeowners are willing to pay an amount equal to their expected payout"

She assesses several explanations: adverse selection, moral hazard, public bail-outs, credit constraints, and **behavioral frictions (e.g., underestimation of flood risk)**

[source: https://www.krhwagner.com/papers/Adaptation%20and%20Adverse%20Selection%20in%20Markets%20for%20Natural%20Disaster%20Insurance%20-%20Katherine%20Wagner.pdf]

Conclusions

- Health insurance reduces financial risks by **reducing out-of-pocket medical expenses and unpaid medical bills**

- **Health insurance in the US does NOT insure against reductions in earnings**, and Americans are "under-insured" to these risks compared to many European countries

- Millions of Americans gained health insurance as a result of the ACA, but **millions of Americans remain uninsured**

  <u>Outstanding puzzle in US:</u> Many uninsured Americans choose to remain uninsured despite the positive effects on financial well-being and evidence of positive effects on health and *extremely* generous subsidies. Why is this happening?

  <u>Additional puzzle:</u> Low WTP may not be specific to health insurance, but may extend to other types of insurance, as well (e.g., flood insurance)

Conclusions

- Health insurance reduces financial risks by **reducing out-of-pocket medical expenses and unpaid medical bills**

- **Health insurance in the US does NOT insure against reductions in earnings**, and Americans are "under-insured" to these risks compared to many European countries

- Millions of Americans gained health insurance as a result of the ACA, but **millions of Americans remain uninsured**

  Outstanding puzzle in US: Many uninsured Americans choose to remain uninsured despite the positive effects on financial well-being and evidence of positive effects on health and *extremely* generous subsidies. Why is this happening?

  Additional puzzle: Low WTP may not be specific to health insurance, but may extend to other types of insurance, as well (e.g., flood insurance)

Thanks!

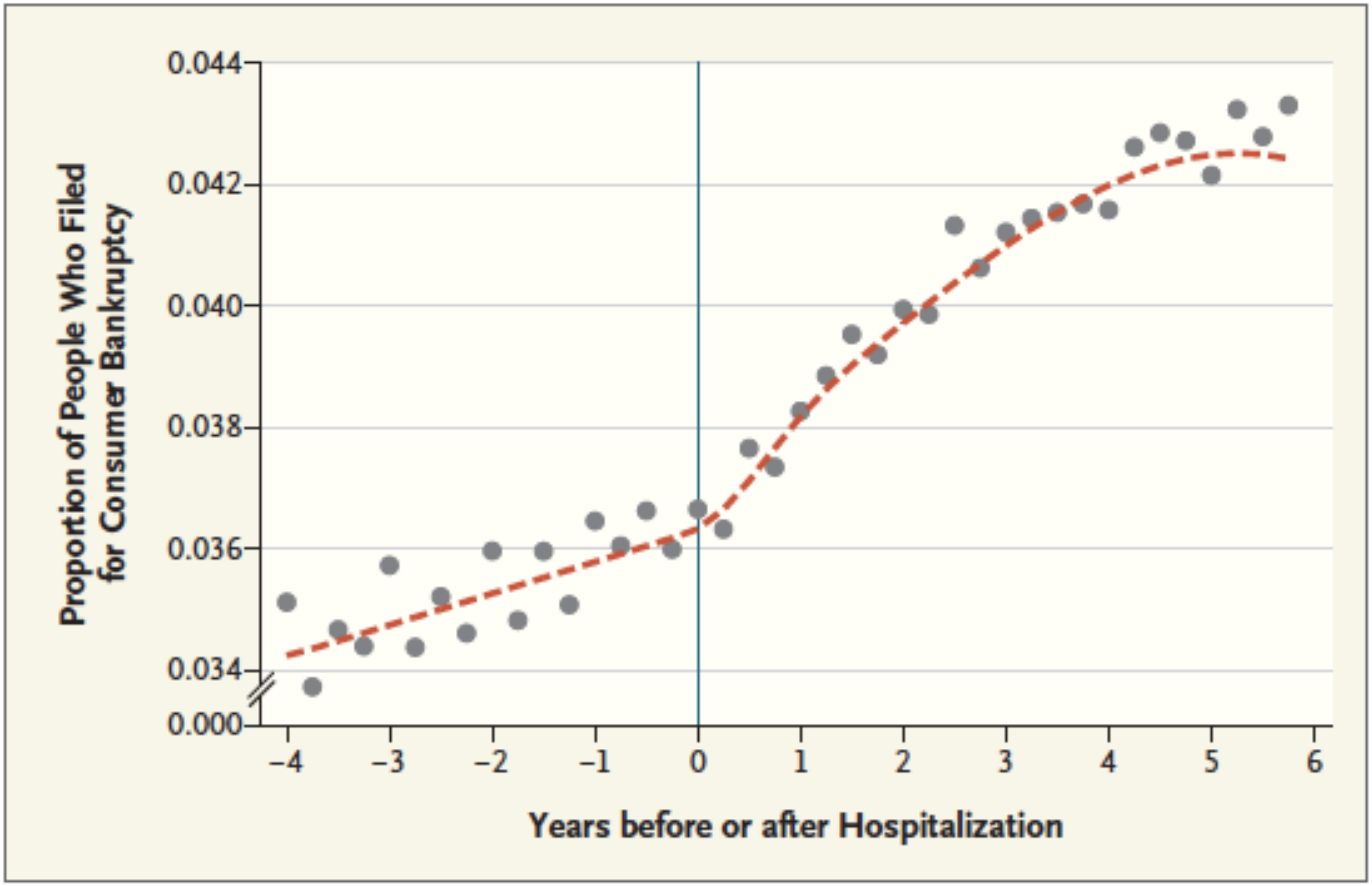
Bonus slides

Effect of Medicare on distribution of out of pocket spending

Centile	Out of pocket spending (ages 65–74 in 1963)	Centile treatment estimates			
		Individuals 55–74		Individuals 55–90	
		Overall (no covariates)	Overall (covariate-adjusted)	Overall (no covariates)	Overall (covariate-adjusted)
(1)	(2)	(3)	(4)	(5)	(6)
75	304	−105	−46	−78*	−31
76	326	−124*	−74	−94*	−56
77	395	−185**	−97	−104*	−64
78	422	−185**	−91	−97*	−84
79	456	−213**	−99	−154**	−136
80	512	−251**	−155	−171**	−129*
81	563	−278**	−183*	−201**	−183*
82	563	−314**	−191**	−305**	−218**
83	580	−279**	−197**	−258**	−178**
84	675	−347**	−278**	−280**	−206**
85	703	−368**	−341**	−344**	−252**
86	816	−452**	−410**	−382**	−310**
87	844	−499**	−400*	−454**	−380*
88	957	−459**	−347**	−414**	−336**
89	1002	−447**	−478**	−393**	−363**
90	1097	−608**	−531**	−587**	−464**
91	1463	−922**	−771*	−812**	−695**
92	1304	−937**	−825**	−935**	−785**
93	1711	−1064**	−951**	−1131**	−1031**
94	2127	−1291**	−1289*	−1363**	−1349**
95	2324	−1000*	−1094	−1415**	−1546**
96	2954	−1274*	−1208	−1384**	−1312**
97	3641	−1166	−1144	−1246	−1177
98	4637	−1090	−1309	−932	−1069
99	5599	−2444	−2527	−2940	−3236

Health insurance and financial well-being

Dobkin, Finkelstein, Kluender, Notowidigdo NEJM 2018 study of medical bankruptcy



<u>Aside:</u> "medical bankruptcy" debate

- Himmelstein, <u>**(Elizabeth) Warren**</u>, Thorne, and Woolhandler (2005) have widely-cited estimate that ~60% of bankruptcies are "medical bankruptcies"
- By contrast, we estimate ~5% of bankruptcies are medical bankruptcies based on our hospitalizations data
- Interesting contrast of methodologies: debtor surveys and interviews vs. statistical models of counterfactual outcomes
- Assumption in Himmelstein et al. is that whenever a person filing for bankruptcy reports substantial medical bills, the bankruptcy was <u>caused</u> by the medical bills
- Our view: statistical fallacy is "assuming that when two things occur together, there is a causal relationship between them"

[See more at https://berniesanders.com/medical-bankruptcy/]

Finkelstein et al. QJE

TABLE VII

FINANCIAL STRAIN (ADMINISTRATIVE DATA)

	Control mean (1)	ITT (2)	LATE (3)	*p*-values (4)
Panel A: Overall				
Any bankruptcy	0.014	0.0022	0.0086	[0.106]
	(0.119)	(0.0014)	(0.0053)	{0.358}
Any lien	0.021	0.0012	0.0047	[0.406]
	(0.144)	(0.0014)	(0.0056)	{0.698}
Any judgment	0.064	0.0014	0.0054	[0.573]
	(0.244)	(0.0024)	(0.010)	{0.698}
Any collection	0.500	−0.012	−0.048	[0.003]
	(0.500)	(0.0041)	(0.016)	{0.013}
Any delinquency (credit accounts)	0.366	0.0016	0.0063	[0.704]
	(0.482)	(0.0042)	(0.017)	{0.698}
Standardized treatment effect		0.0022	0.0086	[0.653]
		(0.0049)	(0.019)	
Panel B: Medical debt				
Any medical collection	0.281	−0.016	−0.064	[<0.0001]
	(0.449)	(0.0040)	(0.016)	{<0.0001}
Amount owed in medical collections	1,999	−99	−390	[0.028]
	(6733)	(45)	(177)	{0.025}
Standardized treatment effect		−0.026	−0.100	[<0.0001]
		(0.0061)	(0.024)	
Panel C: Nonmedical debt				
Any nonmedical collection	0.392	−0.0046	−0.018	[0.264]
	(0.488)	(0.0041)	(0.016)	{0.455}
Amount owed in nonmedical collections	2,740	−20	−79	[0.751]
	(9,492)	(63)	(248)	{0.752}
Standardized treatment effect		−0.0058	−0.023	[0.325]
		(0.0059)	(0.023)	

What else does health insurance do?

Change in total ED visits

	Expansion States		Non-Expansion States	
	Initial Change	12-Month Change	Initial Change	12-Month Change
All ED	12.21 (9.7 – 14.5)	27.7% (24.3 - 31.2)	1.7% (-0.4 - 4.0)	3.8% (1.0 - 6.7)

We develop two main analytical frameworks for estimating recipient willingness to pay for Medicaid. Our first approach, which we refer to as the "complete-information" approach, requires a complete specification of a normative utility function and estimates of the causal effect of Medicaid on the distribution of all arguments of the utility function. The advantage of this approach is that it does not require us to model the precise budget set created by Medicaid or impose that individuals optimally consume medical care subject to this budget constraint. However, as the name implies, the information requirements are high; it will fail to accurately measure the value of Medicaid unless the impacts of Medicaid on all arguments of the utility function are specified and analyzed.

B. *Complete-Information Approach*

In the complete-information approach, we specify the normative utility function over all its arguments and require that we observe all these both with insurance and without insurance. It is then straightforward to solve equation (3) for $\gamma(1)$.

Assumption 1 (Full utility specification for the complete-information approach). The utility function takes the form

$$\boxed{u(c, h) = \frac{c^{1-\sigma}}{1-\sigma} + \tilde{\phi} h,}$$

where σ denotes the coefficient of relative risk aversion and $\tilde{\phi}$ denotes the marginal utility of health. Scaling $\tilde{\phi}$ by the expected marginal utility of consumption yields the expected marginal rate of substitution (MRS) of health for consumption, ϕ $(=\tilde{\phi}/E[c^{-\sigma}])$.

Our second approach, which we refer to as the "optimization" approach, is in the spirit of the "sufficient-statistics" approach described by Chetty (2009) and is the mirror image of the complete-information approach in terms of its strengths and weaknesses. We reduce the implementation requirements by parameterizing the way in which Medicaid affects the individual's budget set and by assuming that individuals have the ability and information to make privately optimal choices with respect to that budget set. With these assumptions, it suffices to specify the marginal-utility function over any single argument. This is because the optimizing individual's first-order condition allows us to value marginal impacts of Medicaid on any other potential arguments of the utility function through the marginal utility of that single argument. To make inferences about nonmarginal changes in an individual's budget set (i.e., covering an uninsured individual with Medicaid), we require an additional statistical assumption that allows us to interpolate between local estimates of the marginal impact of program generosity. This substitutes for the structural assumptions about the utility function in the complete-information approach.

TABLE 2
SUMMARY STATISTICS

	Full Sample (1)	Treatment Compliers ($q = 1$) (2)	Control Compliers ($q = 0$) (3)	Impact of Medicaid (4)
	A. Oregon Data Demographics			
Share female	.60	.57	.60	
Share age 50–64	.34	.36	.35	
Share age 19–49	.66	.64	.65	
Share white	.83	.84	.84	
Share black	.03	.03	.03	
Share Spanish/Hispanic/Latino	.11	.07	.08	
Mean family size, n	2.97	2.88	2.91	
	B. Oregon Data Outcomes			
12-month medical spending, m:				
Mean medical spending, $E[m]$ ($)	2,991	3,600	2,721	879
Fraction with positive medical spending, $E[m > 0]$	.74	.79	.72	.07
12-month out-of-pocket spending, x:				
Mean out-of-pocket spending, $E[x]$ ($)	470	0	569	−569
Fraction with positive out-of-pocket spending, $E[x > 0]$	.38	0	.56	−.56
Health expressed in QALYs, $E[h]$	.77	.78	.74	.05
Share in poor health (QALY = .401)	.11	.10	.17	−.07
Share in fair health (QALY = .707)	.30	.29	.36	−.07
Share in good health (QALY = .841)	.36	.38	.28	.10
Share in very good health (QALY = .931)	.17	.18	.15	.03
Share in excellent health (QALY = .983)	.05	.05	.04	.02

TABLE 3

WILLINGNESS TO PAY (WTP) FOR MEDICAID BY RECIPIENTS

		Optimization Approaches	
	Complete-Information Approach (1)	Consumption-Based (Consumption Proxy) (2)	Consumption-Based (CEX Consumption Measure) (3)
	A. Recipient WTP for Medicaid		
$\gamma(1)$ (standard error)	1,675 (60)	1,421 (180)	793 (417)
Transfer component, T	569–863	661	661
Pure-insurance component, I	812–1,106	760	133
	B. Benchmarks		
Net costs as fraction of gross cost, C/G	.40	.40	.40
Recipient WTP as fraction of net cost, $\gamma(1)/C$	1.16	.98	.55
Moral hazard cost, $G - T - N$	585–879	787	787

NOTE.—Estimates of WTP and moral-hazard costs are expressed in dollars per year per Medicaid recipient. Standard errors are bootstrapped with 500 repetitions.

Mahoney AER

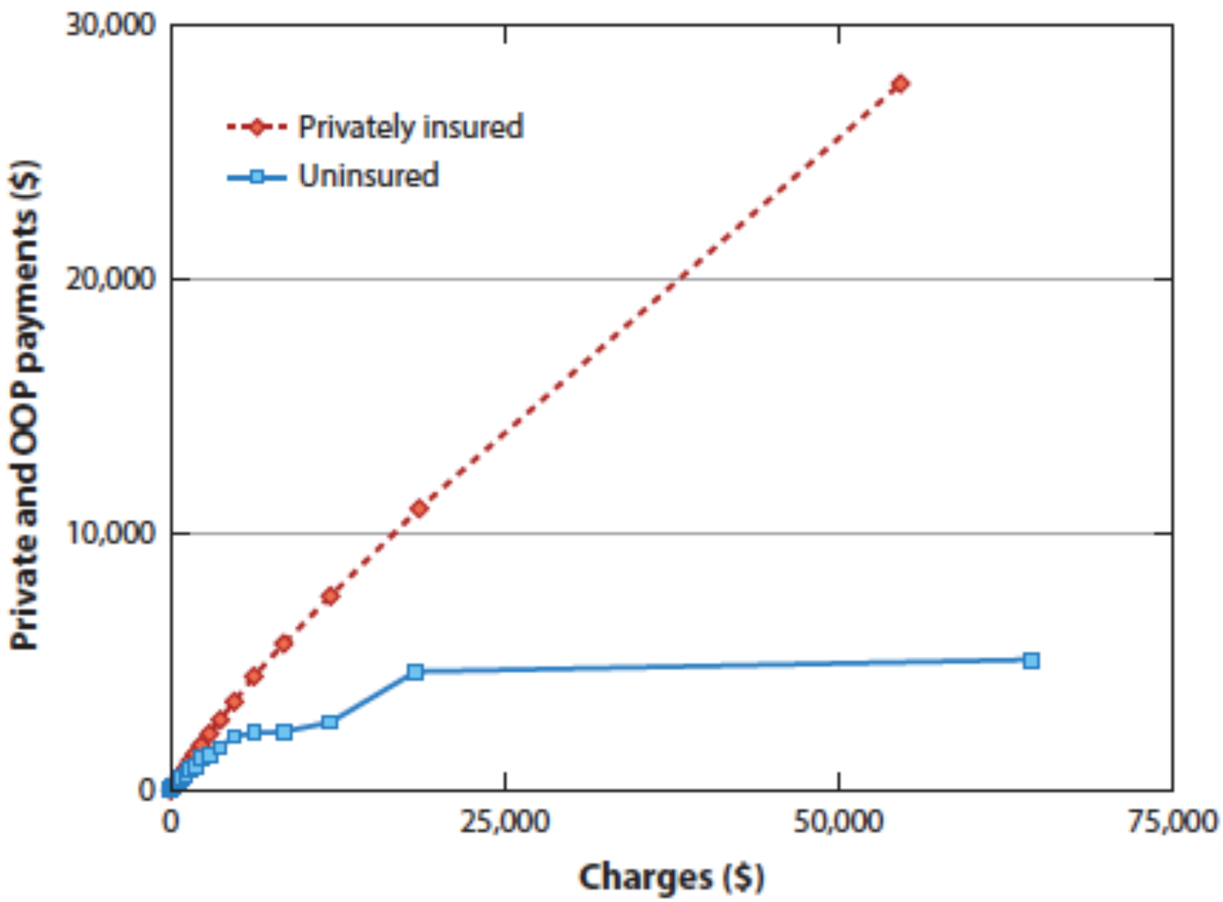


Figure 1

Payments plotted against charges for privately insured and uninsured households. Payments are the sum of out-of-pocket (OOP) payments and payments from private insurance providers. (Payments by the uninsured are therefore simply OOP payments.) Charges are the list price of medical care and proxy for the level of medical utilization. The plot was created by averaging payments and charges at 20ths of the charge distribution. Pooled 1996–2005 Medical Expenditure Panel Surveys, excluding households with public insurance or a member age 65 or older, are inflation adjusted to 2005 US dollars using the CPI-U. Figure reproduced with permission from Mahoney (2015, figure 1*A*).

Mahoney AER

Hartford Hospital
80 Seymour St.
Hartford, CT 06102
(860) 545-5000

In order to process your application for Financial Assistance, we need the following information from you:

- Copies of income received (pay stubs, pension, unemployment, alimony, child support, interest, dividends, rental income, etc.) and most current W2 form
- Letter that you have been denied state assistance
- Letter from person providing food and shelter
- Letter from person assisting with bills
- Letter from person whose bills are in their name
- Most recent asset statements
  - Savings and checking account statements
  - Tax shelter, bonds, stocks, trust funds, TSA, IRA's, money market, CD, etc.
- Year and model of car(s) owned and estimated value
- Estimated value of home and outstanding balance
- Monthly/Outstanding debts
  - Most recent rent/mortgage/house taxes not included in mortgage payment receipts
  - Medical bills
  - Credit card statements (past 3 months with payments)
  - Loan, Insurance, and Taxes paid and outstanding balances
  - Utility bills (past 3 months with payments)
- Any additional information you would like to include____________________

Please forward as much information as possible within ten (10) Business Days so that we can facilitate the application process and mail all forms to you at the address that you provide in your application. If you need assistance completing the application, please contact us.

For-Profit versus Non-Profit Hospitals
Hospitals as Insurers of Last Resort
Cost-Shifting in Hospitals

AEA Continuing Education Program
CLASS #4

Matthew J. Notowidigdo ("Noto")
David McDaniel Keller Professor of Economics
University of Chicago Booth School of Business
Co-Director, Chicago Booth Healthcare Initiative
Co-Scientific Director, J-PAL North America
Research Associate, National Bureau of Economics Research

Outline

- For-profit versus Non-profit hospitals
- Hospitals as Insurers of Last Resort
- The Samaritan’s Dilemma
- Cost-Shifting in Hospitals

Outline

- **For-profit versus Non-profit hospitals**
- Hospitals as Insurers of Last Resort
- The Samaritan’s Dilemma
- Cost-Shifting in Hospitals

Fairview Hospital

Product/Service Involved	Date of Purchase	Amount of Purchase
OUR JOB	N/A	N/A

What do you want the company to do?

Explanation of Problem:

We were told if we don't get money from patients in the emergency room we will be fired!

Fairview Hospital

- Fairview hospital is a non-profit hospital in Minnesota that worked with consultants to find ways to get patients to pay “up front” (prior to receiving care)
- Consultants also developed new strategies for collecting debts from patients
- This resulted in federal lawsuit and plenty of bad press for Fairview, perhaps in part because Fairview is a **non-profit hospital**
- Some broad questions for today: What makes non-profit hospitals different? How do we understand their behavior?

Non-profit, for-profit, and public hospitals

Most hospitals in the U.S. are private hospitals, and most private hospitals are organized as non-profit organizations

- In 2021, there were 5,141 community hospitals in the US (short-term, non-federal, general hospitals)
  - 2,946 private, non-profit (57%)
  - 1,233 private, for-profit (24%)
  - 962 public (19%)

- In 2011, 20% of hospitals were private, for-profit hospitals and 22% of hospitals were public hospitals

Non-profits in the healthcare sector

- In 33 states, the largest non-profit organization is a healthcare organization
- As measured by operating margin, many of the most-profitable hospitals are non-profit hospitals
- The 5 largest non-profits in the country are all healthcare-related organizations:
    1. Kaiser foundation (OR)
    2. Dignity health (CA)
    3. UPMC (PA)
    4. Cleveland clinic foundation (OH)
    5. Banner health (AZ)

Costs and benefits of non-profit status

Benefits:

- Preferential tax treatment (e.g., exempt from corporate income taxes, property taxes, etc.)
- Can raise money from donors who receive tax deductions from their donations

Costs:

- Cannot sell stock to investors directly (but can raise capital in debt capital markets instead of equity capital markets)
- Cannot distribute profits to owners or shareholders
- Restricted to certain charitable activities

Determinants of non-profit status

Large variation across states:

- Nevada (54%), Texas (52%), Florida (48%) have many for-profit hospitals
- Rhode Island, New York, and Minnesota have no for-profit hospitals (due to restrictive ownership laws)
- Wyoming (68%), Iowa (50%), Kansas (44%) have many public hospitals, while North Dakota and New Hampshire don't have any public hospitals

https://www.aha.org/system/files/media/file/2021/01/Fast-Facts-2021-table-FY19-data-14jan21.pdf

https://web.archive.org/web/20111018090804/http://www.aha.org/research/rc/stat-studies/101207fastfacts.pdf

https://www.kff.org/other/state-indicator/hospitals-by-ownership/?dataView=0&currentTimeframe=0&sortModel=%7B%22colId%22:%22For-Profit%22,%22sort%22:%22desc%22%7D

Requirements of non-profits

1. Activities should be directed towards (tax-exempt) purpose that serve a public interest, not a private interest

2. Lobbying activities are allowed but cannot be “substantial” (“expenditure test”)

3. Prohibited from directly or indirectly participating in any political campaign

4. Cannot generate too much income from activities unrelated to the exempt function of non-profit organization

5. Annual reporting obligation and must operate “in accord with stated (tax-exempt) purpose”

Existing economic theories of non-profits

- Non-profits are simply “for-profits in disguise”
- Mechanism for entrepreneurs to express altruistic preferences (“pure altruism”)
- Non-profits represent a cooperative effort by key employees to gain control of the organization (e.g., non-profit hospitals as “physician cooperatives”)
- Non-profits represent a strategic response to non-contractible quality (e.g., non-profits can “signal” an interest in quality over profits)

Broader non-profit trends

- Over the last several decades, non-profits have grown as a share of economy, increasing from 1% to 6% of GDP

[Non-profit firms are quite common in both healthcare and education, which are both growing as a share of GDP]

- In consumer banking, non-profit banks are typically organized as credit unions (CUs), which are a large (and growing) share of the consumer banking sector:
  - 26% of personal loans
  - 13% of mortgages
  - 25% of auto loans

[Aside] Non-profit credit unions (CUs)

- (Former Chicago Booth PhD student) Andrés Shahidinejad finds in his dissertation that CUs charge lower interest rates, price in less risk-sensitive ways, and are less likely to resell originated mortgages to the secondary market
- He also finds "banking with a CU" causes consumers to have fewer unpaid bills, higher credit scores, and a lower risk of bankruptcy.
- He concludes that his empirical evidence goes against the view that CUs are simply "for-profits in disguise"

https://bpb-us-w2.wpmucdn.com/sites.northeastern.edu/dist/6/2602/files/2023/04/BCU_v3.pdf

[Review] DRG-based reimbursement

- DRG = diagnosis-related group (e.g., “pneumonia”)

- Large Medicare reform in 1983 shifted from [retrospective] fee-for-service reimbursement to [prospective] lump-sum DRG-based reimbursement

- At first, ~500 DRGs; by 2008, expanded to ~750 DRGs

[Review] DRG-based reimbursement

Many studies have found that this major reform led to a remarkable and sudden drop in number of days that Medicare patients spent in the hospital (figure below from Gross-Noto textbook)

Upcoding DRGs in for-profit vs. non-profit hospitals

- **Upcoding** refers to the strategic response to provider payments based on diagnosis codes (**DRGs**)
- Can look at trends in upcoding as changes in share of pneumonia diagnoses coded as more-complex case (Gram-negative versus Gram-positive)
- Key idea: as long as physicians reasonably suspected Gram-negative pneumonia, **upcoding** patients is a profit-enhancing strategy
- Silverman and Skinner JHE 2004 write: *"For upcoding to occur, administrators must be willing to engage in risky but potentially profitable behavior, and physicians must acquiesce by approving (and, until 1995, signing) the DRG claims submitted by hospital to Medicare"*

Upcoding in for-profit vs. non-profit hospitals

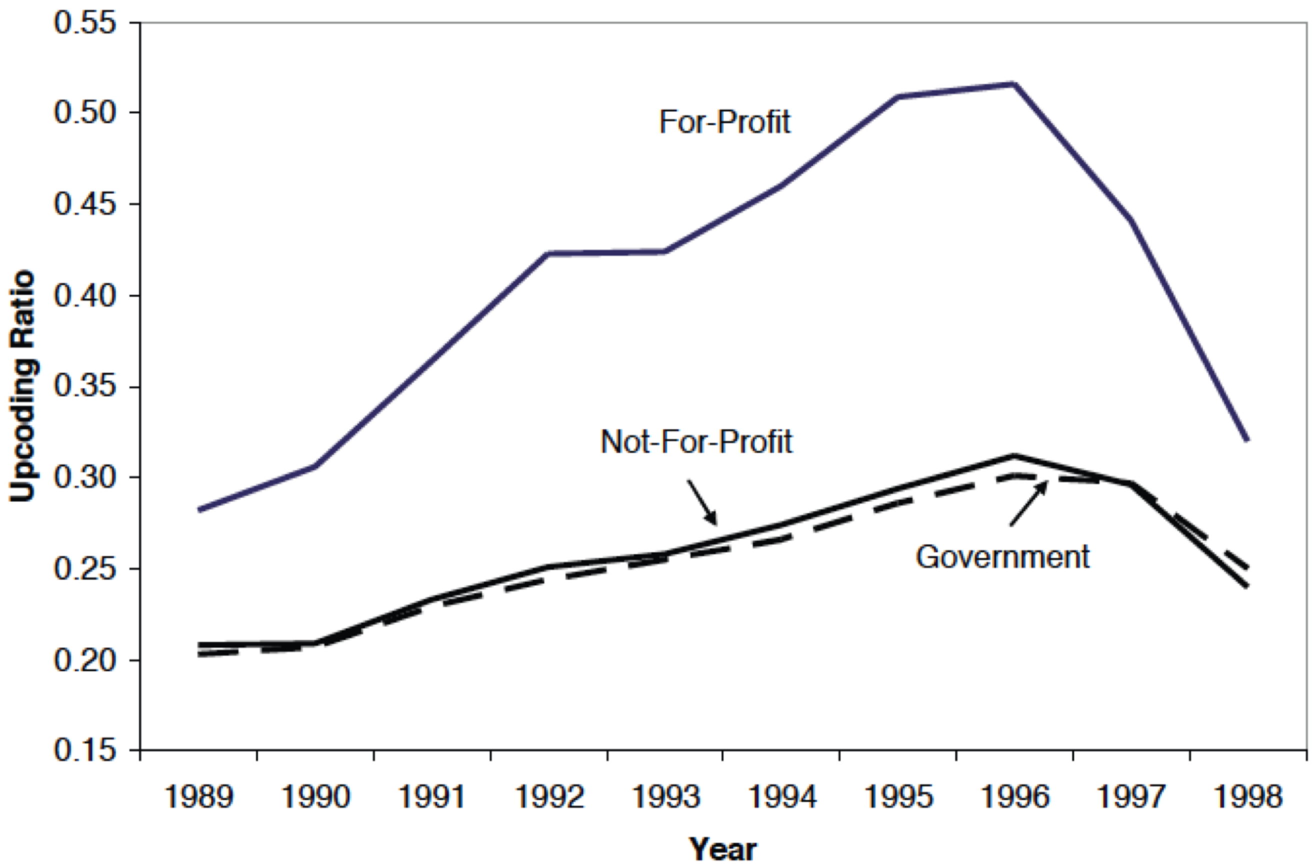


Fig. 1. The upcoding ratio by ownership status of hospital, 1989–1998. *Note*: All hospitals exhibit stable ownership patterns (for-profit, not-for-profit, and government) in 1989, 1993, and 1996. Upcoding is measured as the ratio of DRG 79 to the sum of DRGs 79, 80, 89, and 90.

Upcoding in for-profit vs. non-profit hospitals

- Reimbursement for Gram-positive pneumonia was $6,000 (versus $8,000 for Gram-negative)
- <u>Risky strategy!</u> In 1996, DOJ investigated the practice and sued hospitals
- Similar behavior observed today in Medicare Advantage (relative to traditional Medicare)
- Additional anecdotal evidence in the Silverman-Skinner paper:

> *"When one formerly non-profit hospital was purchased by Columbia [for-profit hospital chain now called HCA], within a year the percentage of pneumonia patients with the most expensive DRG jumped from 31 to 76%"*

[Source: https://linkinghub.elsevier.com/retrieve/pii/S0167629603001206]

Hospital responses to payment changes

Regulated Revenues and Hospital Behavior: Evidence from a Medicare Overhaul

Tal Gross, Adam Sacarny, Maggie Shi, David Silver

> Author and Article Information

The Review of Economics and Statistics 1–26.

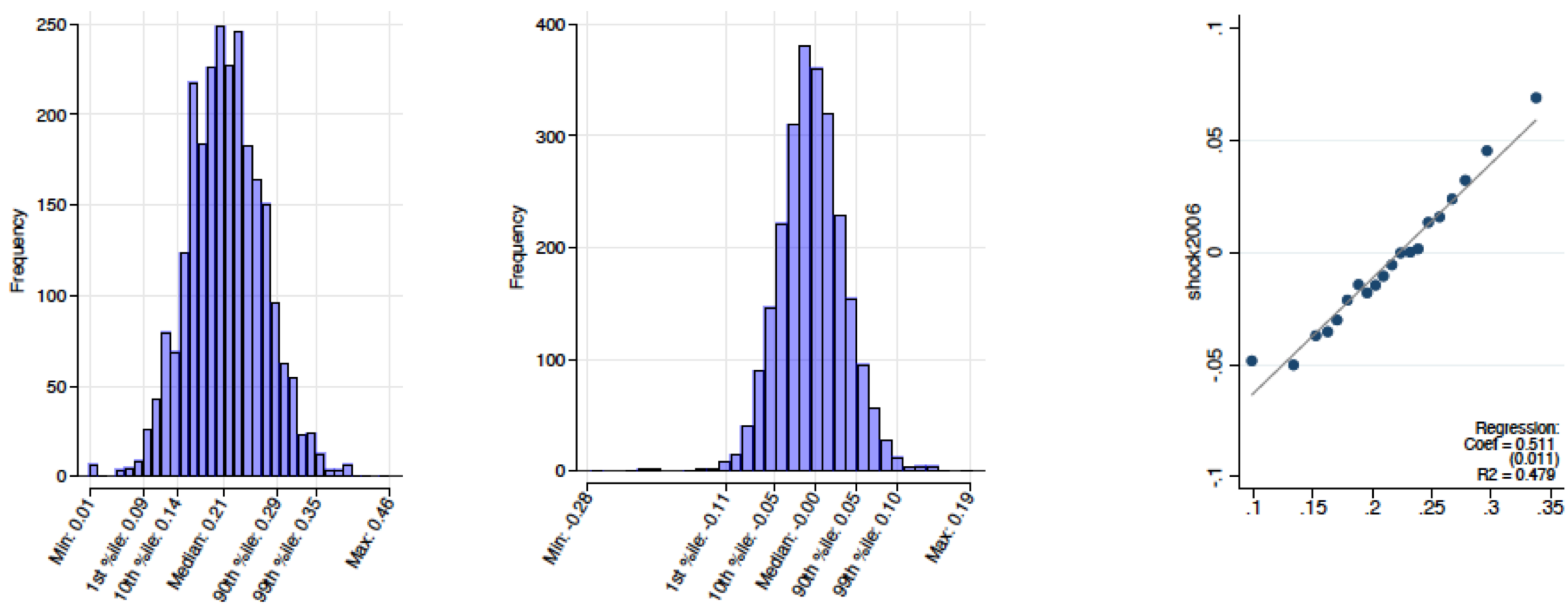
https://doi.org/10.1162/rest_a_01254

We study a 2008 policy reform in which Medicare revised its hospital payment system to better reflect patients' severity of illness. We construct a simulated instrument that predicts a hospital's policy-induced change in reimbursement using pre-reform patients and post-reform rules. The reform led to large persistent changes in Medicare payment rates across hospitals. Hospitals that faced larger gains in Medicare reimbursement increased the volume of Medicare patients they treated. The estimates imply a volume elasticity of 1.2. To accommodate greater volume, hospitals increased nurse employment, but also lowered length of stay.

Hospital responses to payment changes

Figure 1. Determinants and Distribution of the Revenue Shock

(a) Share MCC in 2006 (b) SHOCK_h (c) Bivariate Relationship

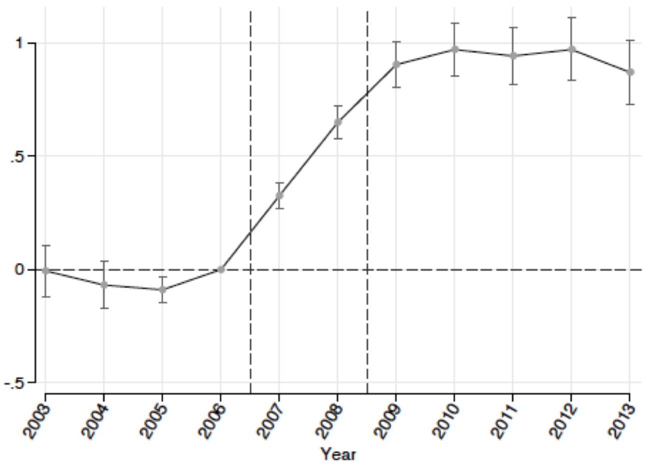


These figures show the linkage between a hospital's share of patients with major complications and comorbidities (MCCs) and its revenue shock.

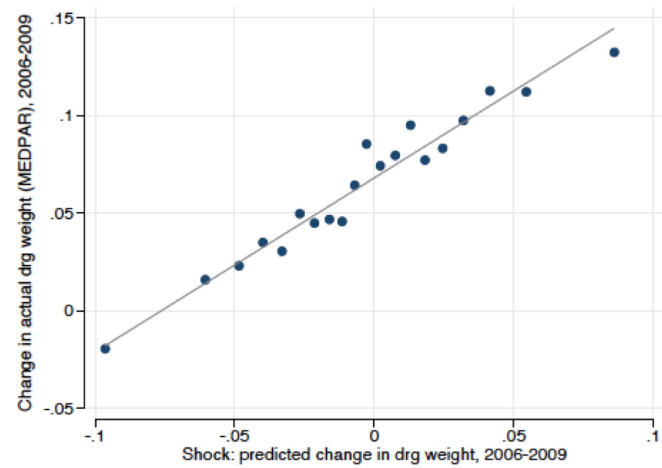
Hospital responses to payment changes

Figure 2. Pass Through and First Stage

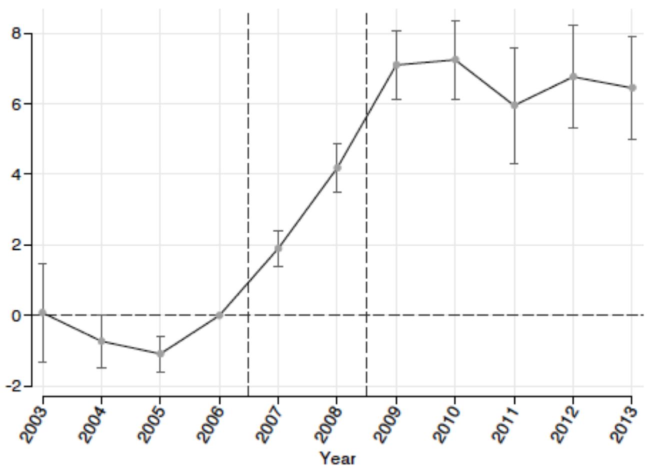
(a) Pass Through: DRG Weight, Event Study



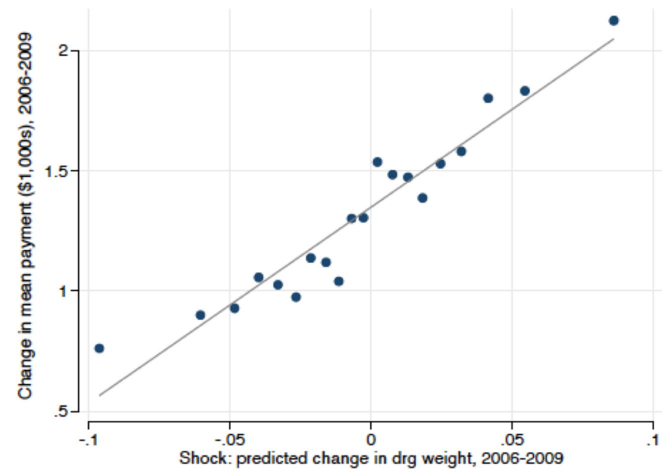
(b) Pass Through: DRG Weight, Binned Scatterplot



(c) First Stage: Payment ($1,000s), Event Study



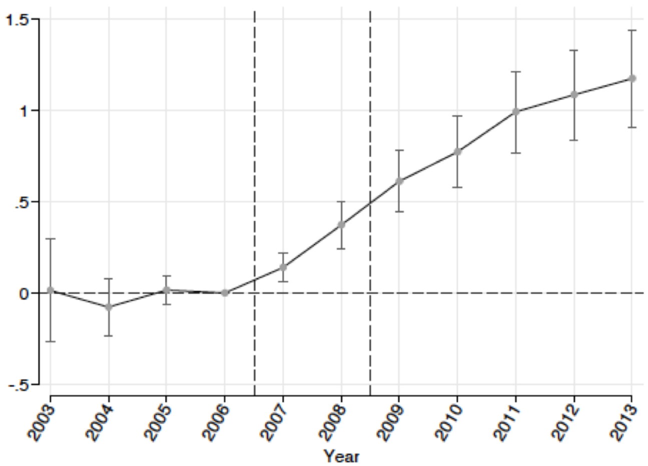
(d) First Stage: Payment ($1,000s), Binned Scatterplot



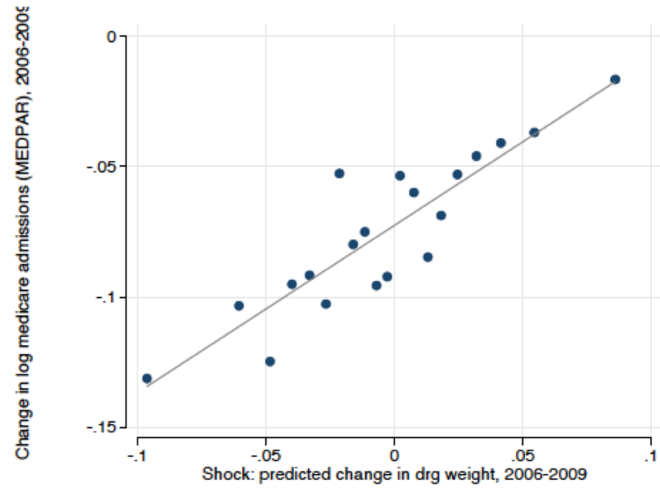
Hospital responses to payment changes

Figure 3. Reduced-Form Effects

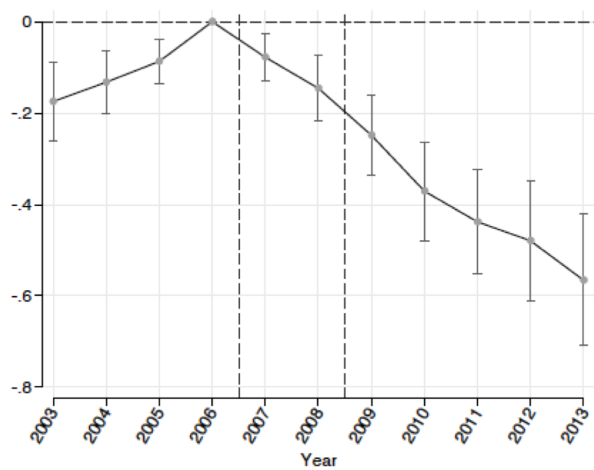
(a) Log Medicare Volume, Event-Study



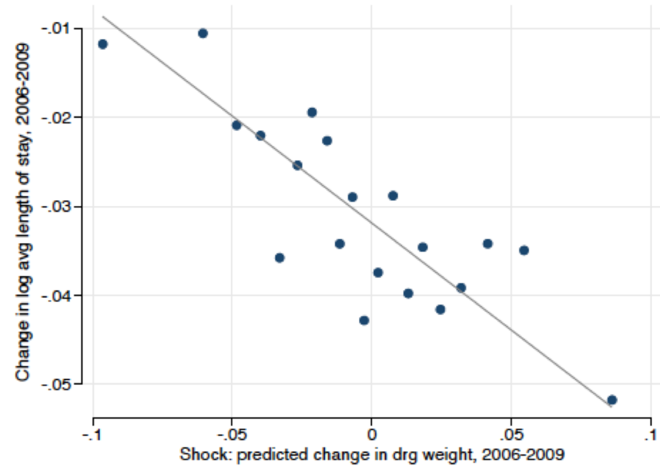
(b) Log Medicare Volume, Binned Scatterplot



(c) Log Medicare Length of Stay, Event-Study



(d) Log Medicare Length of Stay, Binned Scatterplot



Hospital responses to payment changes

Table 2. Impact of Revenue Shock on First Stage, Hospital Volume, and Resources – unweighted

	Reduced Form	IV	N	Hospitals
	A. Pass Through			
DRG Weight	0.974***		27,575	2,508
	(0.061)			
	B. First Stage			
Medicare Payment ($1,000s)	7.134***		27,575	2,508
	(0.667)			
	C. Logged Hospital Volume and Throughput			
Medicare Volume (MEDPAR data)	0.939***	0.130***	27,575	2,508
	(0.125)	(0.020)		
Medicare Length of Stay	-0.322***	-0.045***	27,575	2,508
	(0.061)	(0.010)		
Medicare Volume (AHA data)	1.202***	0.170***	27,263	2,502
	(0.135)	(0.024)		
Medicaid Volume	0.794***	0.112***	27,236	2,502
	(0.223)	(0.033)		
Other Volume	0.308*	0.043*	27,282	2,504
	(0.179)	(0.025)		

Hospital responses to payment changes

Table 2. Impact of Revenue Shock on First Stage, Hospital Volume, and Resources – unweighted

	Reduced Form	IV	N	Hospitals
	A. Pass Through			
DRG Weight	0.974***		27,575	2,508
	(0.061)			
	B. First Stage			
Medicare Payment ($1,000s)	7.134***		27,575	2,508
	(0.667)			
	D. Logged Hospital Scale Measures			
Beds	0.330***	0.046***	27,326	2,504
	(0.124)	(0.018)		
Full-time Equivalents	0.357***	0.050***	27,325	2,504
	(0.117)	(0.016)		
Nurses Employed	0.497***	0.070***	27,310	2,504
	(0.125)	(0.018)		
Payroll	0.239**	0.034**	27,326	2,504
	(0.116)	(0.016)		

Hospital responses to payment changes

Table A1. Effects of the Revenue Shock by Hospital Ownership

	(1) Average Total Payment ($1000s)	(2) Log Medicare Volume	(3) Log Medicare Volume	(4) Log Medicare Length of Stay	(5) Log Medicare Length of Stay
For profit × Revenue Shock × Post	8.356***	0.816***		-0.781***	
	(1.623)	(0.281)		(0.150)	
Non profit × Revenue Shock × Post	6.609***	0.860***		-0.193***	
	(0.825)	(0.147)		(0.063)	
Government × Revenue shock × Post	6.770***	1.356***		-0.183	
	(1.875)	(0.329)		(0.137)	
For profit × Average Total Payment ($1000s)			0.0931***		-0.0935***
			(0.0358)		(0.0254)
Non profit × Average Total Payment ($1000s)			0.130***		-0.0292**
			(0.0266)		(0.0114)
Government × Average Total Payment ($1000s)			0.200***		-0.0268
			(0.0703)		(0.0221)
For-profit v. Non-profit	0.34	0.89	0.41	0.00**	0.02**
For-profit v. Government	0.52	0.21	0.18	0.00**	0.05**
Non-profit v. Government	0.94	0.17	0.35	0.94	0.92

BCBS plans converting from non-profit to for-profit

- Blue Cross and Blue Shield merged in 1982 [BCBS]
- Congress revoked BCBS federal tax exemption as part of 1986 TRA
- Between 1994 and 2003, 14 BCBS plans converted to for-profit stock corporations
- Many plans cited access to equity capital markets as “key driver” of their desire to convert
- Policy concern that conversions would ultimately produce premium increases (and also concern over other factors like executive bonuses)

[Source: https://www.aeaweb.org/articles?id=10.1257/pol.20130370]

Congress revoked BCBS federal tax exemption as part of 1986 TRA

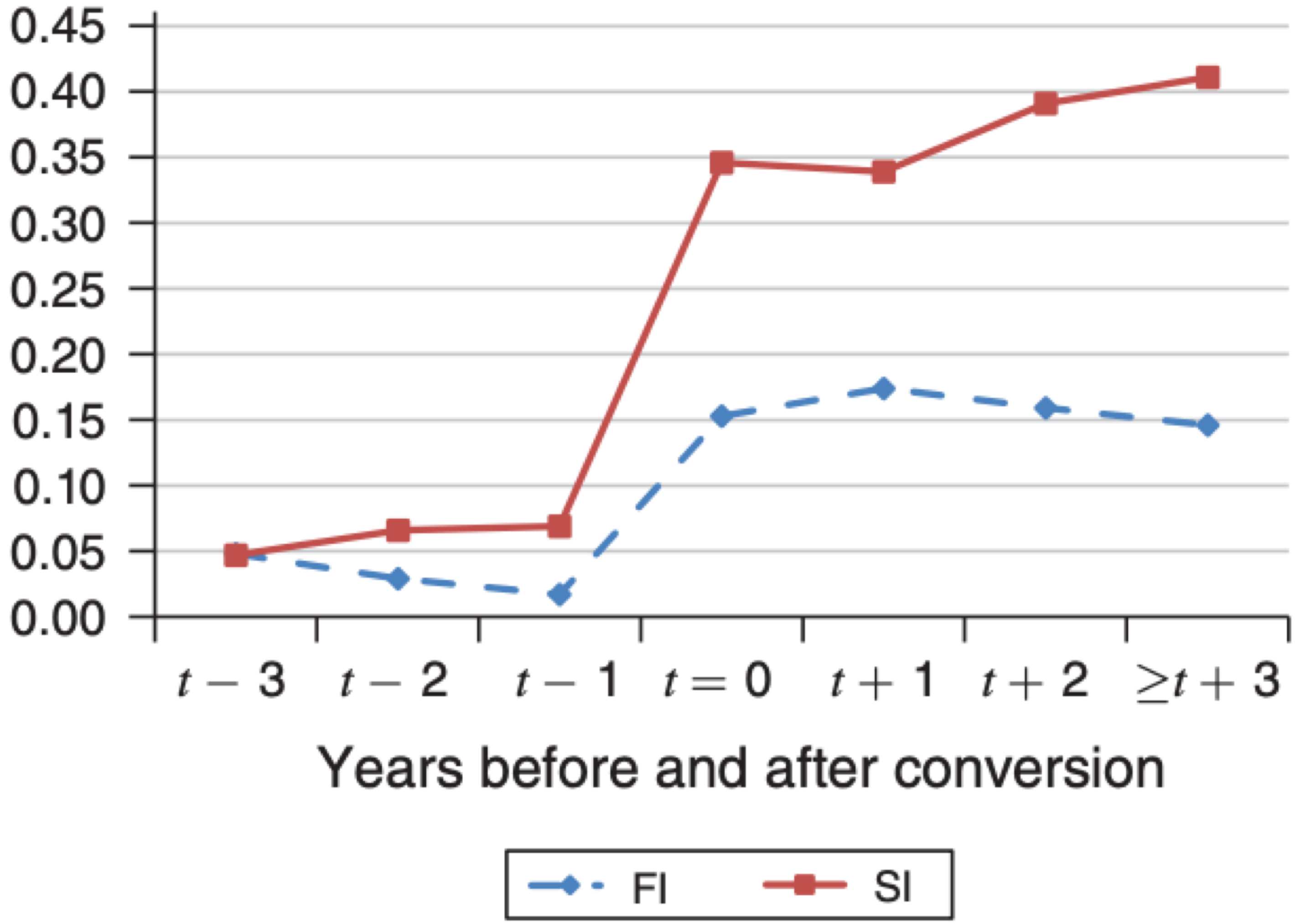
The differences between Blue Cross-Blue Shield health insurance plans and commercial health insurers may not be great enough to justify Blue Cross-Blue Shield's tax-exempt status, the General Accounting Office has concluded

Blue Cross-Blue Shield and commercial insurers 'offered similar, although limited, coverage to high-risk individuals.' The report also said Blue Cross-Blue Shield and commercial insurers used similar pricing methods for most of their business and that Blue Cross's price-setting policies for high-risk individuals 'have come to resemble' those used by commercial insurers.

[Source: https://www.nytimes.com/1986/07/04/us/blue-cross-tax-status-is-challenged.html]

BCBS plans converting from non-profit to for-profit

For-profit market share



[Aside] Self-insured vs. Fully-insured employer plans

Is self-insurance right for you?

Self-insurance is also called a self-funded plan. This is a type of plan in which an employer takes on most or all of the costs of benefit claims. The insurance company manages the payments, but the employer is the one who pays the claims.

[Aside] Self-insured vs. Fully-insured employer plans

Benefits of self-insurance

These plans are often more flexible for you as the employer because you may not be subject to certain state requirements, and at the end of the plan year, you can get money back.

Self-insurance offers you the flexibility to meet health care challenges and allows you to better manage health care costs.

And you still get the benefit of a network of providers – doctors, hospitals and specialists – with contracts that help determine prices.

[Aside] Self-insured vs. Fully-insured employer plans

- Risk-neutral firms maximize expected profits, and risk neutrality implies that firms are not willing to pay for insurance that reduces uncertainty in costs => **firms will "self-insure" and not pay risk premium to insurance company**

- Longer run trend in self-insurance:

  [1998] 40.9% of private-sector workers enrolled in self-insured plans

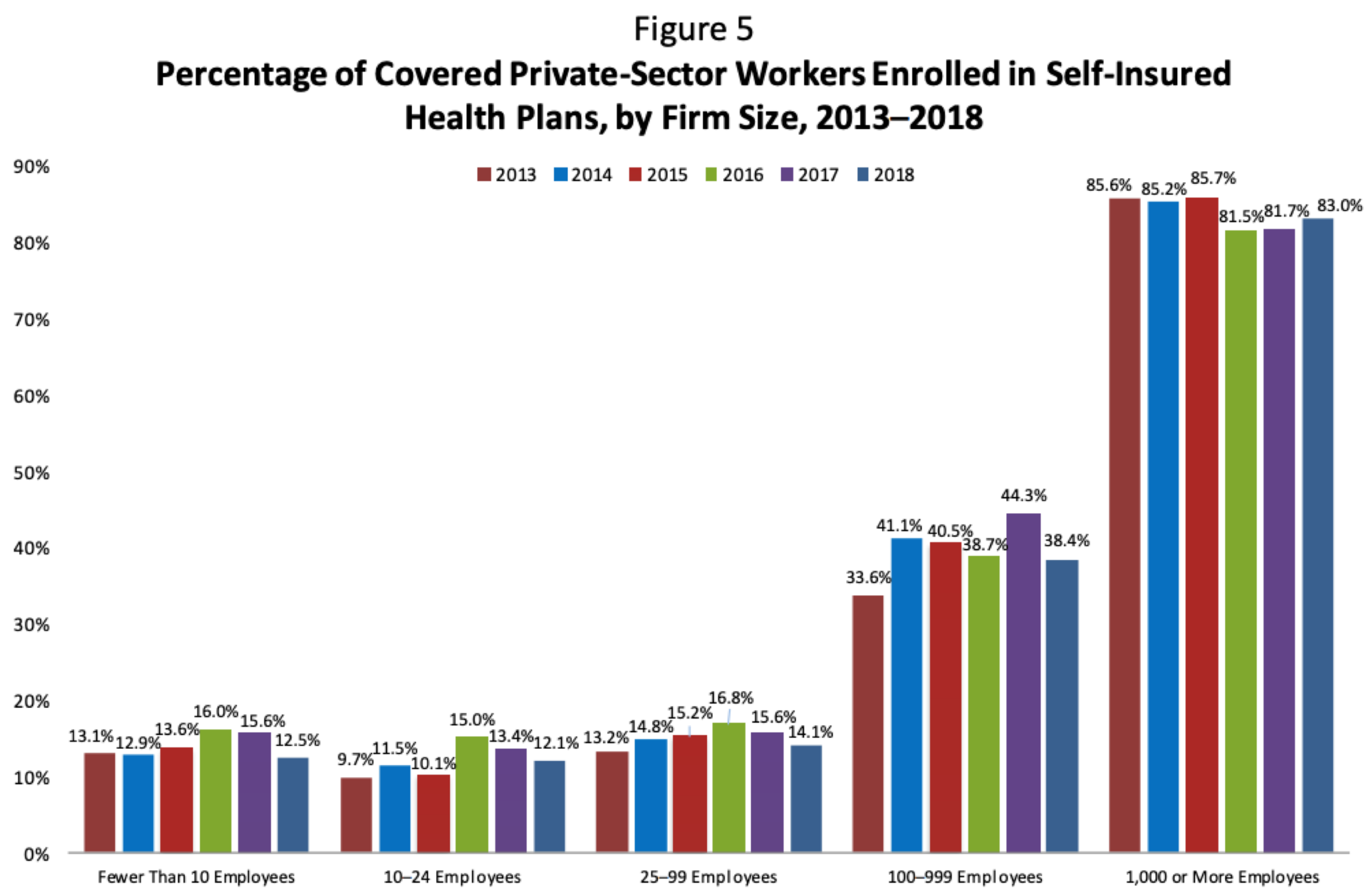
  [2018] 58.7% of private-sector workers enrolled in self-insured plans

- Variation across states:

  [CA] 43.4% of private-sector workers enrolled in self-insured plans

  [OH] 72.0% of private-sector workers enrolled in self-insured plans

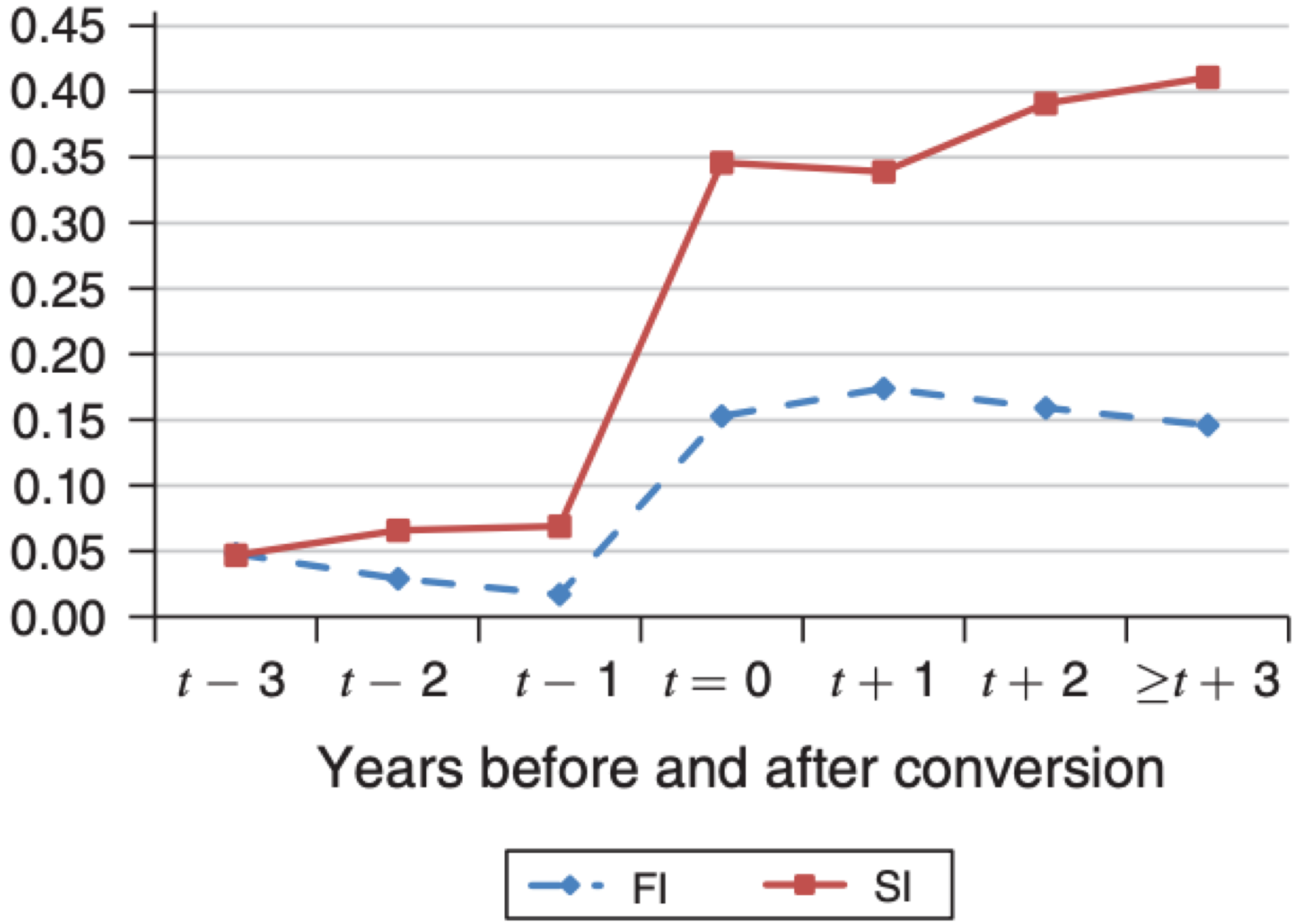
[Aside] Self-insured vs. Fully-insured employer plans



Source: Various tables from the Medical Expenditure Panel Survey-Insurance Component that can be found at http://meps.ahrq.gov/mepsweb/data_stats/quick_tables.jsp

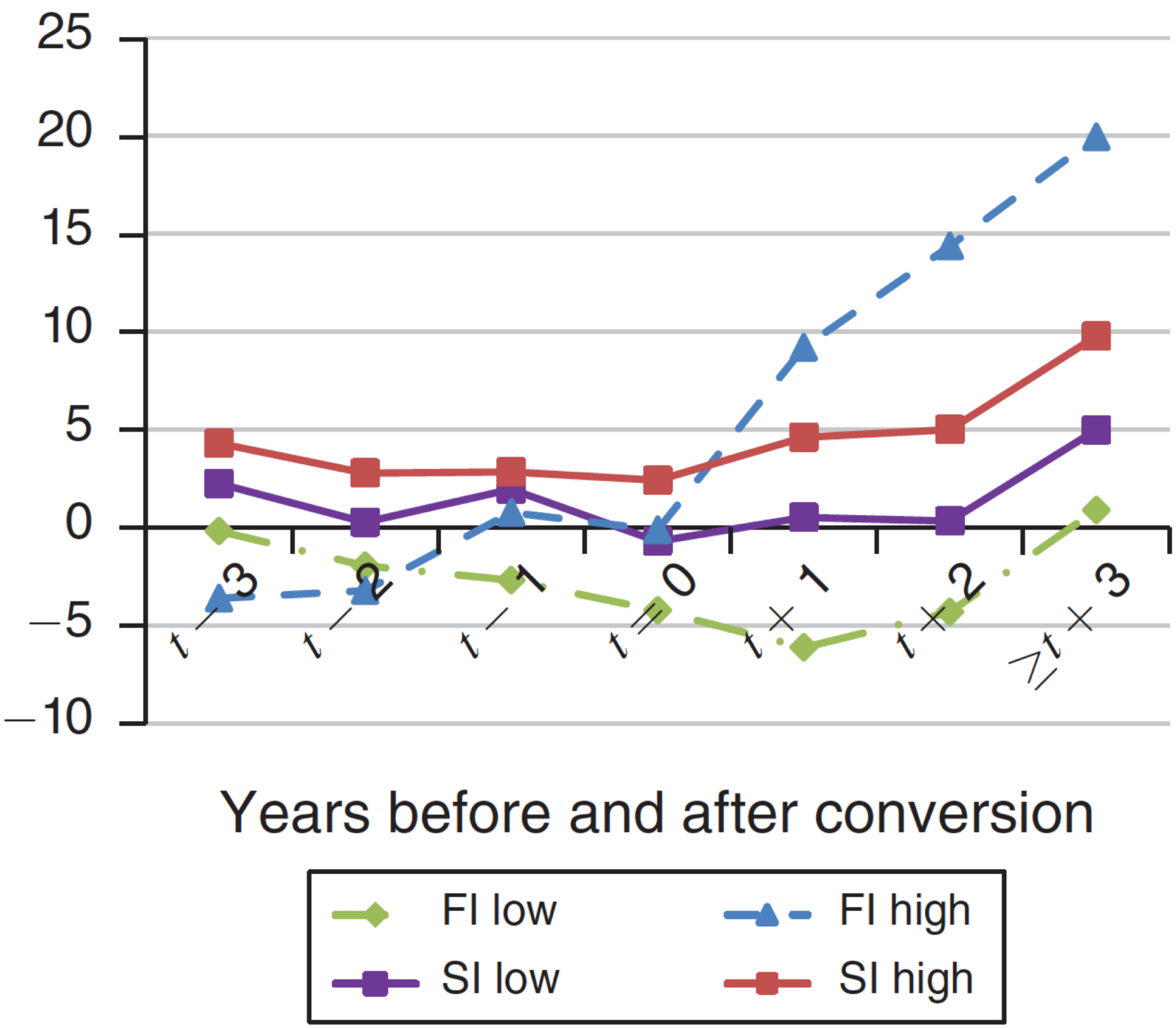
BCBS plans converting from non-profit to for-profit

For-profit market share



BCBS plans converting from non-profit to for-profit

FIGURE 5. EFFECT OF BCBS CONVERSIONS ON PREMIUMS



Notes: "high" and "low" refers to market concentration; "FI" and "SI" refers to fully-insured and self-insured market segments

BCBS plans converting from non-profit to for-profit

- A very large share of large employers are self-insured, and market share of for-profit insurers is particularly high in self-insured segment
- Dafny finds that the BCBS-conversion-induced increases in premiums did not lead to increases in the uninsurance rate, but did lead to increases in Medicaid enrollment
- [Noto's note] The estimated increases in premiums <u>may</u> partly reflect improvements in plan quality
- Today, non-profit insurers continue to express interest in converting into for-profit firms

Outline

- **For-profit versus Non-profit hospitals**
- Hospitals as Insurers of Last Resort
- The Samaritan’s Dilemma
- Cost-Shifting in Hospitals

Outline

- For-profit versus Non-profit hospitals
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Background on **uncompensated care**

Hospitals in the US provide health care to the uninsured for a variety of reasons:

1. Emergency Medical Treatment and Active Labor Act (EMTALA)

2. Non-profit status

3. Medical ethics

   Doctors are taught to be "good Samaritans" – doctors are taught to treat people in need regardless of their ability to pay

EMTALA and unpaid medical bills

- As a result of EMTALA, when uninsured individuals visit hospitals needing emergency medical treatment, hospitals are required to treat those patients
- The hospital can seek payment, but many of the bills are left unpaid. The resulting care that hospitals provide without compensation is called **uncompensated care**

  Total hospital uncompensated care is ~$40B-$50B a year, which is both a large share of Medicaid hospital spending (~30%) and a large share of hospital profits (~70%)

- Hospitals can (and often do) turn to collection agencies

[From Class #1] Unpaid medical bills are a large share of all unpaid bills on consumer's credit reports

Background on **uncompensated care**

“People have access to health care in America. After all, you just go to an emergency room.”

- George W. Bush, July 2007

“Well, we do provide care for people who don’t have insurance. If someone has a heart attack, they don't sit in their apartment and die. We pick them up in an ambulance, and take them to the hospital, and give them care. And different states have different ways of providing for that care.”

- Mitt Romney, September 2012

Uncompensated care and the Samaritan's dilemma

- How does **uncompensated care** relate to health insurance?
- If an uninsured individual recognizes that they will get emergency medical treatment without having to pay for it, they might conclude that's almost as good as having formal insurance
- Economists use the term "**Samaritan's dilemma**" to describe this kind of situation
- Suppose the federal government would like to subsidize health insurance to make it affordable to everyone, but because the uninsured know they will be taken care of in an emergency, they may choose to remain uninsured <u>even if they are offered very generous subsidies to purchase health insurance</u>

The Samaritan's dilemma

- **Adverse selection** is often cited as a rationale for government involvement in health insurance markets, and a justification for mandating individuals to purchase insurance

- The **Samaritan's dilemma** is another distinct and potentially important rationale for health insurance mandates

Out-of-pocket spending [Mahoney *AER*]

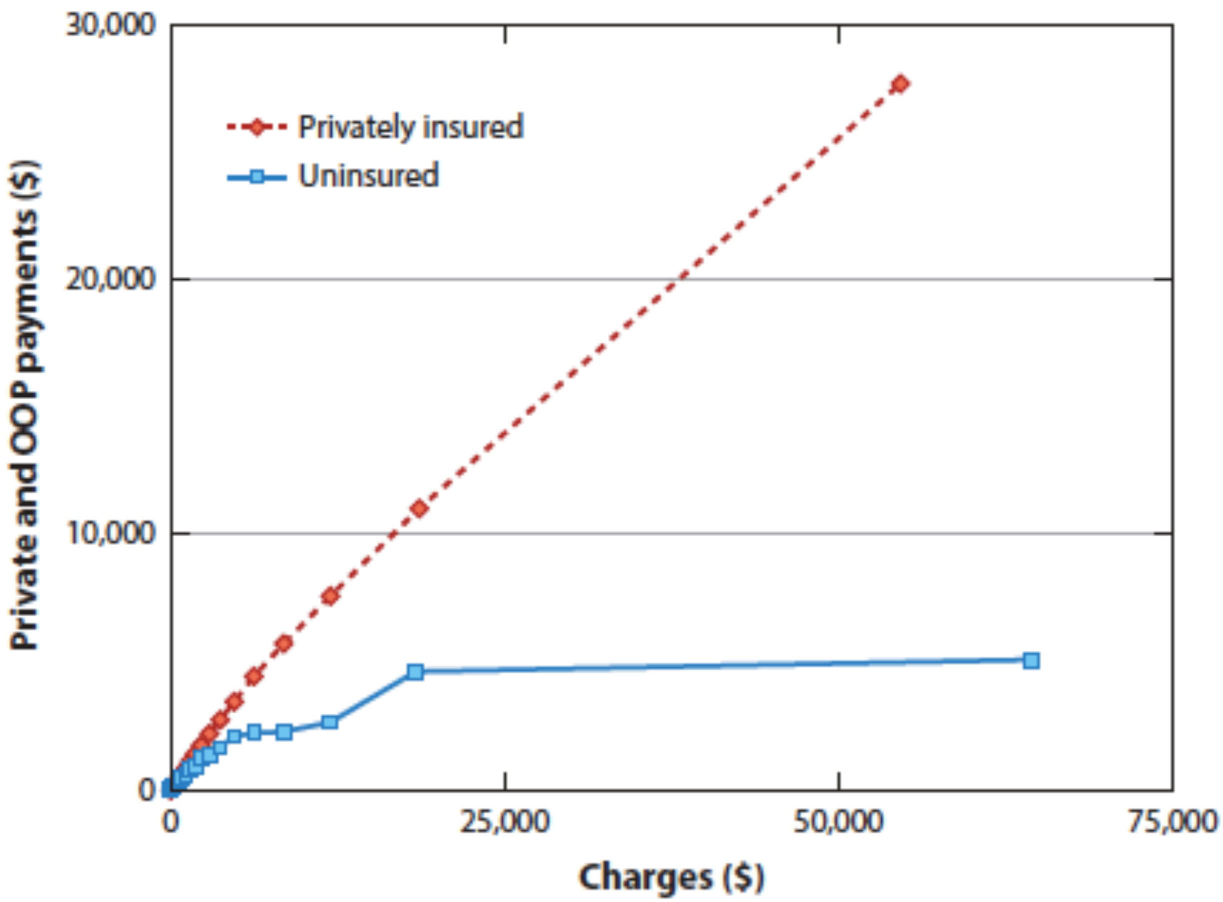

Figure 1

Payments plotted against charges for privately insured and uninsured households. Payments are the sum of out-of-pocket (OOP) payments and payments from private insurance providers. (Payments by the uninsured are therefore simply OOP payments.) Charges are the list price of medical care and proxy for the level of medical utilization. The plot was created by averaging payments and charges at 20ths of the charge distribution. Pooled 1996–2005 Medical Expenditure Panel Surveys, excluding households with public insurance or a member age 65 or older, are inflation adjusted to 2005 US dollars using the CPI-U. Figure reproduced with permission from Mahoney (2015, figure 1*A*).

Hospital financial aid [Mahoney *AER*]

Hartford Hospital
80 Seymour St.
Hartford, CT 06102
(860) 545-5000

In order to process your application for Financial Assistance, we need the following information from you:

- Copies of income received (pay stubs, pension, unemployment, alimony, child support, interest, dividends, rental income, etc.) and most current W2 form
- Letter that you have been denied state assistance
- Letter from person providing food and shelter
- Letter from person assisting with bills
- Letter from person whose bills are in their name
- Most recent asset statements
  - Savings and checking account statements
  - Tax shelter, bonds, stocks, trust funds, TSA, IRA's, money market, CD, etc.
- Year and model of car(s) owned and estimated value
- Estimated value of home and outstanding balance
- Monthly/Outstanding debts
  - Most recent rent/mortgage/house taxes not included in mortgage payment receipts
  - Medical bills
  - Credit card statements (past 3 months with payments)
  - Loan, Insurance, and Taxes paid and outstanding balances
  - Utility bills (past 3 months with payments)
- Any additional information you would like to include____________________

Please forward as much information as possible within ten (10) Business Days so that we can facilitate the application process and mail all forms to you at the address that you provide in your application. If you need assistance completing the application, please contact us.

[Incidence]
Who ultimately pays for hospital uncompensated care?

*"To pay for [uncompensated care], health care providers **pass on the cost** to private insurers, which **pass on the cost** to families."*

- Text of Affordable Care Act

*"Hospitals **pass on the cost** [of uncompensated care] to insurers through higher rates, and insurers, in turn, **pass on the cost** to policy holders in the form of higher premiums."*

- Chief Justice Roberts

Health insurance and hospital uncompensated care costs

Hospitals as Insurers of Last Resort†

By Craig Garthwaite, Tal Gross, and Matthew J. Notowidigdo*

American hospitals are required to provide emergency medical care to the uninsured. We use previously confidential hospital financial data to study the resulting uncompensated care, medical care for which no payment is received. Using both panel-data methods and case studies, we find that each additional uninsured person costs hospitals approximately $800 each year. Increases in the uninsured population also lower hospital profit margins, suggesting that hospitals do not pass along all uncompensated-care costs to other parties such as hospital employees or privately insured patients. A hospital's uncompensated-care costs also increase when a neighboring hospital closes. (*JEL* G22, I11, I13, L25)

Health insurance and hospital uncompensated care costs

Garthwaite, Gross, Notowidigdo *AEJ-Applied* 2018, <u>"Hospitals as Insurers of Last Resort"</u>

- Data use agreement with the American Hospital Association (AHA) to study previously confidential hospital-level financial data from 1984-2011, including **hospital-level uncompensated care costs**
  - Uncompensated care charges for every AHA hospital
  - Adjust charges using hospital-specific cost-to-charge ratio
  - Adjust all financial outcomes to 2011 dollars

- AHA survey includes detailed financial and non-financial data (e.g., revenue, expenditures, admissions, beds, etc.)

- <u>Main finding:</u> Each uninsured persons costs hospitals approximately $800 each year

Hospital charges

Garthwaite, Gross, Notowidigdo *AEJ-Applied* 2018, "Hospitals as Insurers of Last Resort"

"Hospitals report charges rather than costs. A well-known problem in the study of hospital finance is the growing spread between the list price that hospitals charge for a service and the actual payments these facilities receive from private payers. As a result, charge-based measures of uncompensated care provide an inaccurate description of actual costs"

"For the main estimates, we calculate each hospital's cost-to-charge ratio as its total expenses divided by the sum of gross patient revenue and other operating revenue, and we rely on the average of this measure across years for each hospital. This measure thus provides a way to translate hospital charges into an approximate measure of the average costs of the hospital."

Dependent variable	Per capita uncompensated care			
	(1)	(2)	(3)	(4)
Panel A. All hospitals				
Share of population uninsured	793.37	814.14	841.77	830.51
	(299.71)	(295.10)	(335.49)	(302.37)
	[0.01]	[0.01]	[0.02]	[0.01]
R^2	0.870	0.872	0.889	0.892
Observations	1,224	1,224	1,224	1,224
Panel B. Hospitals with an ED				
Share of population uninsured	797.34	816.90	845.59	832.43
	(308.06)	(304.26)	(349.55)	(315.75)
	[0.01]	[0.01]	[0.02]	[0.01]
R^2	0.864	0.866	0.884	0.887
Observations	1,224	1,224	1,224	1,224
Panel C. Hospitals without an ED				
Share of population uninsured	–4.21	–3.10	–5.04	–3.21
	(11.14)	(11.93)	(17.84)	(17.65)
	[0.71]	[0.80]	[0.78]	[0.86]
R^2	0.480	0.480	0.549	0.551
Observations	1,200	1,200	1,200	1,200

Dependent variable	Per capita uncompensated care			
	(1)	(2)	(3)	(4)
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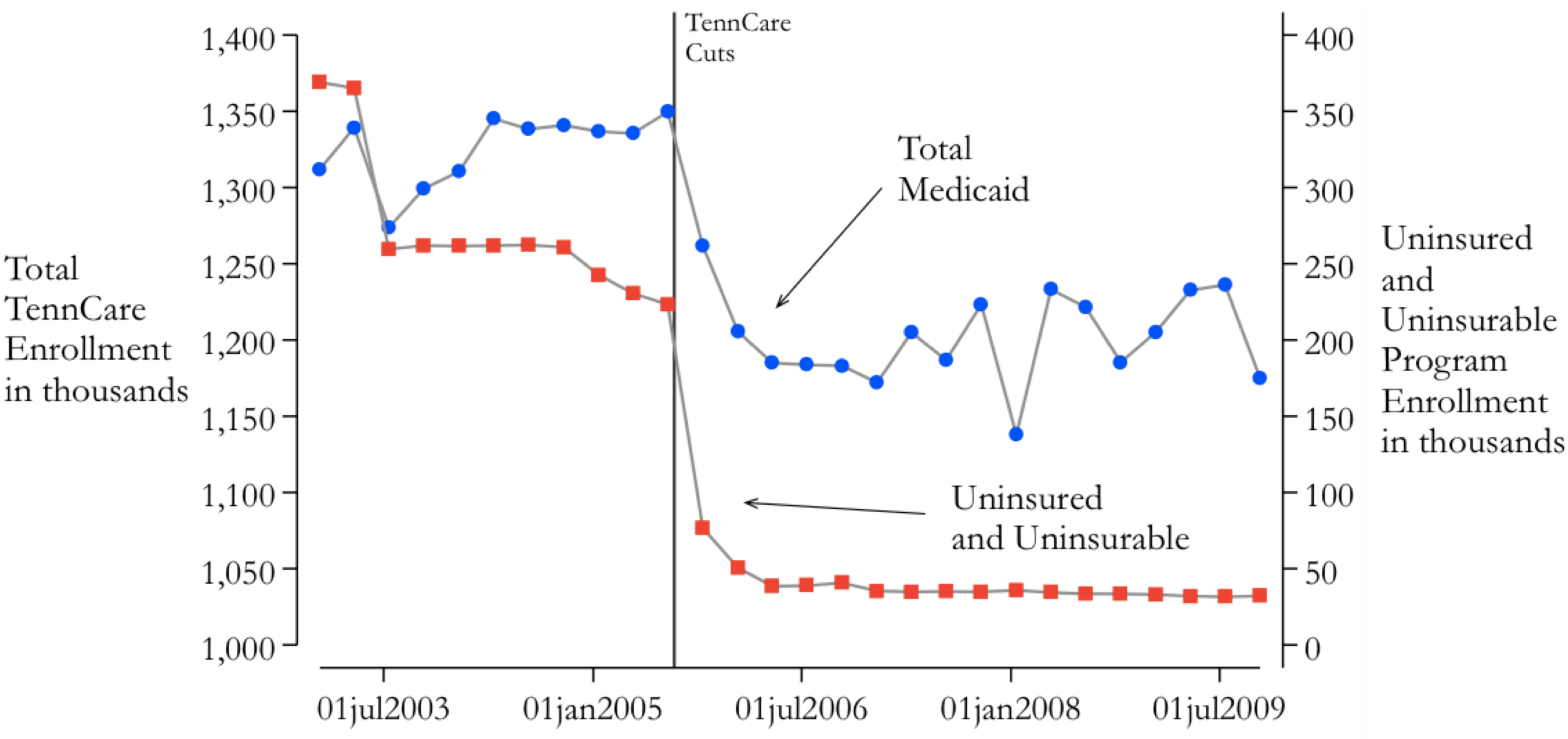
TennCare disenrollment in 2005



TennCare disenrollment in 2005

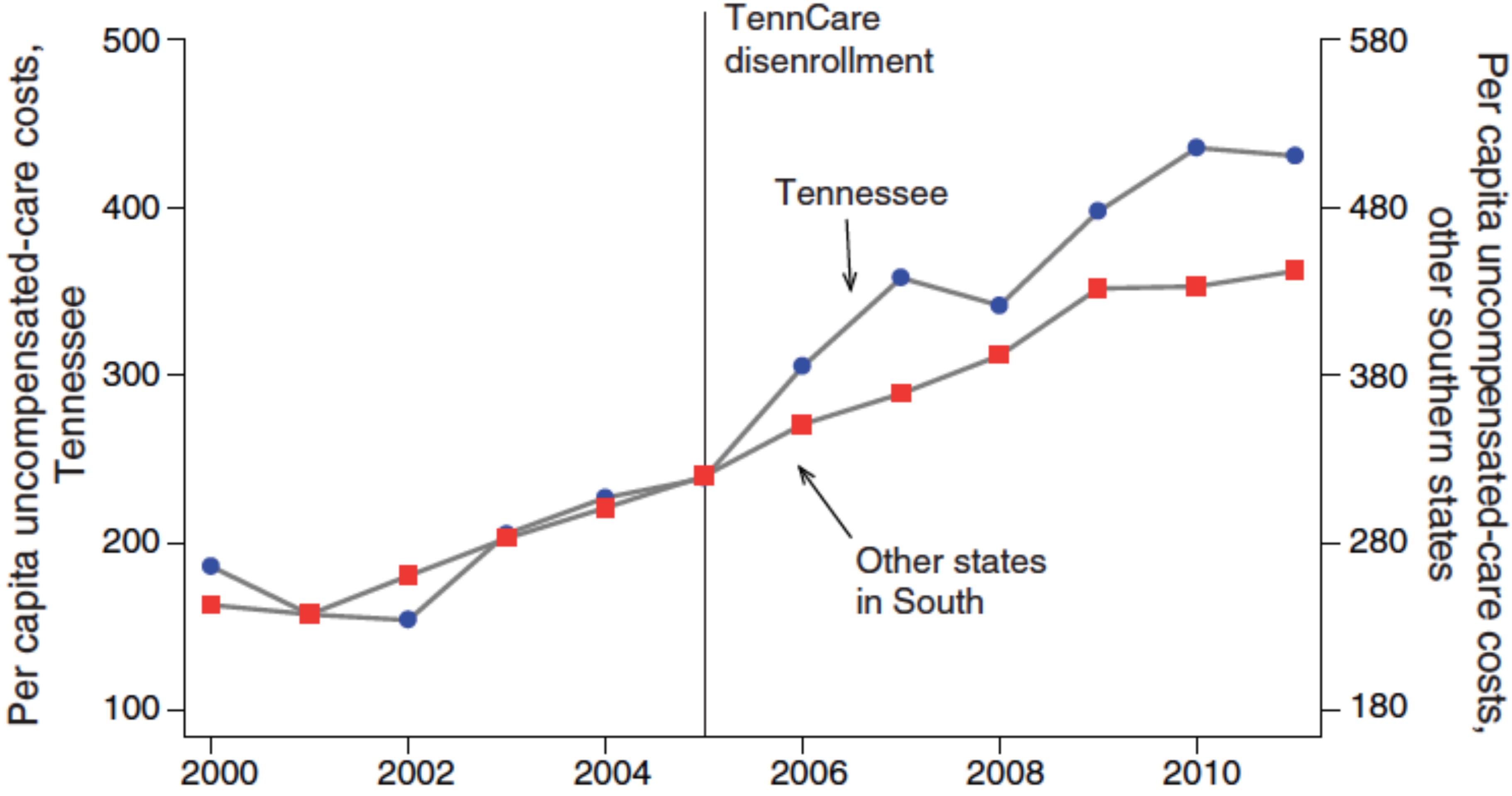
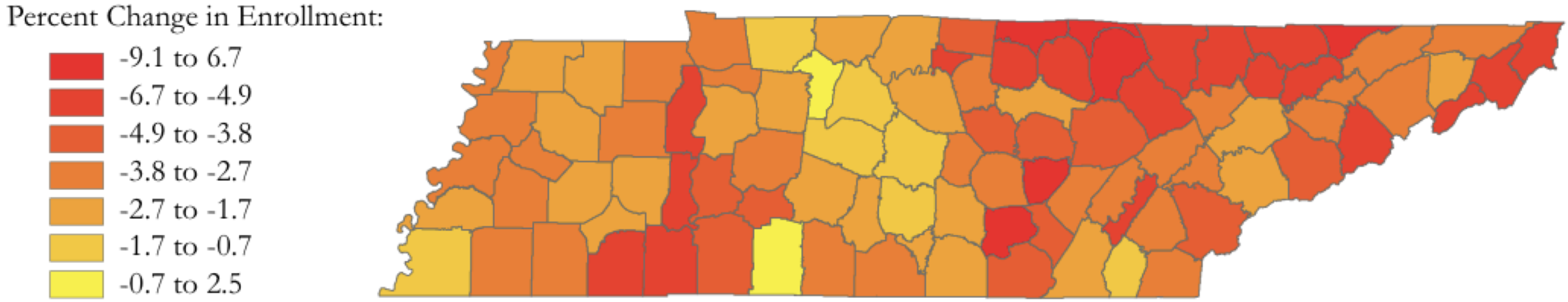


FIGURE 3. UNCOMPENSATED-CARE COSTS IN TENNESSEE

Within-state variation in TennCare disenrollment



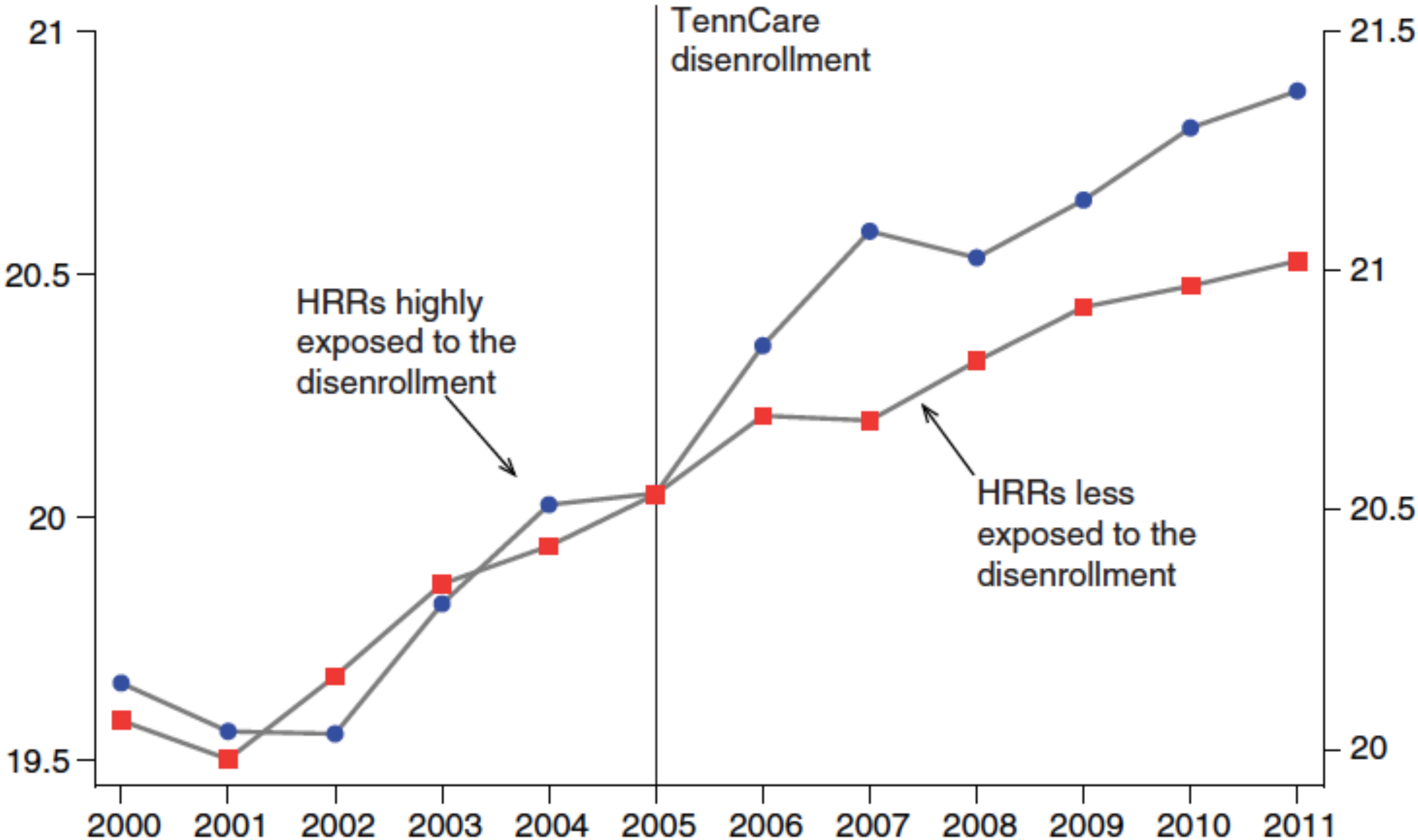


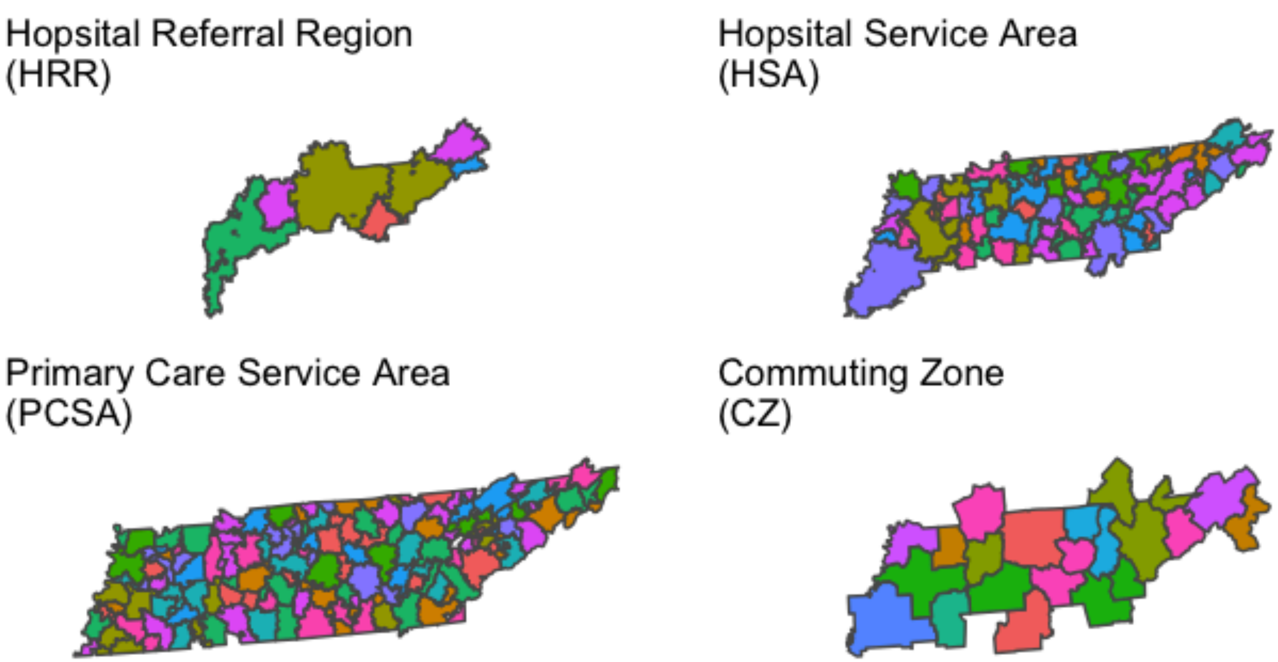
Figure 4. Changes in Uncompensated-Care Costs within Tennessee, AHA Data

[Aside] Alternative hospital market definitions

[Small] County, Health Service Area

[Medium] Commuting Zone

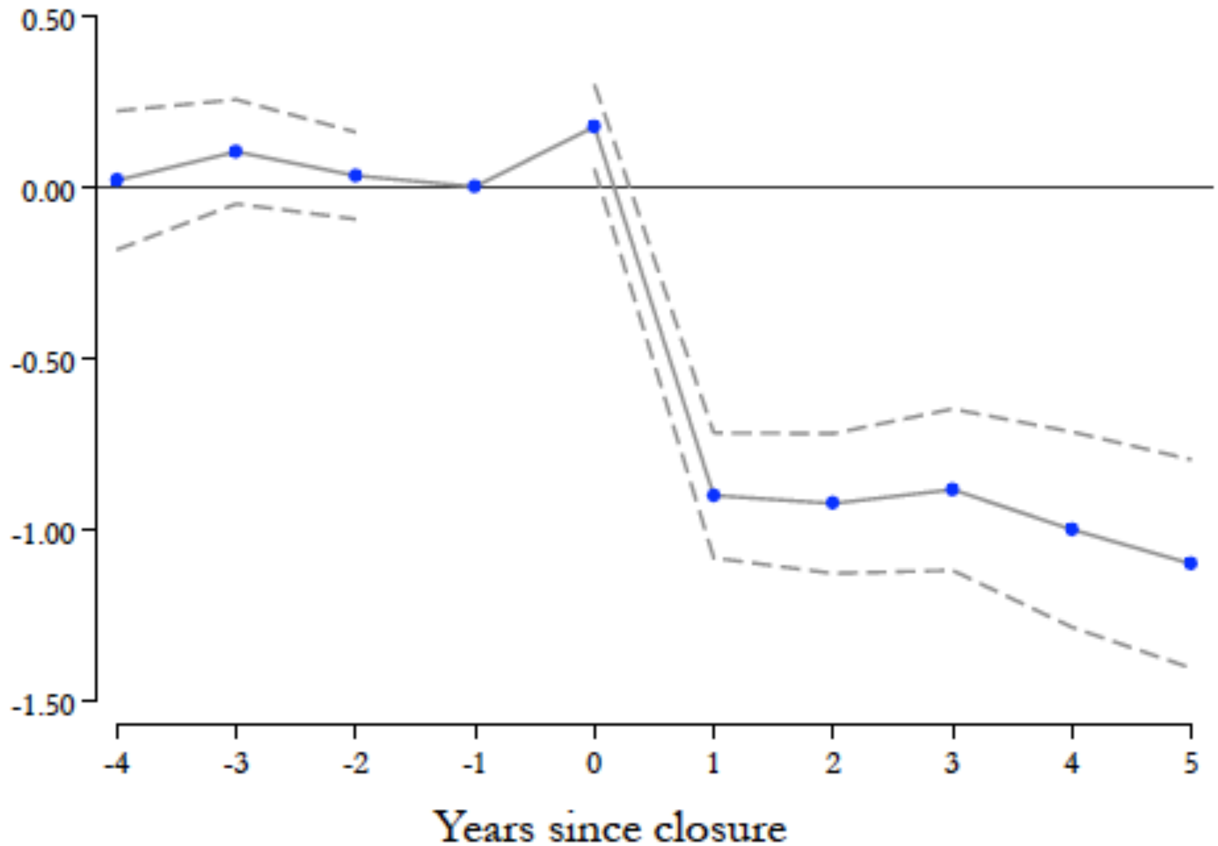
[Large] Hospital Referral Region



<u>Source:</u> https://graveja0.github.io/health-care-markets/

"Hospitals as Insurers of Last Resort" – Additional findings

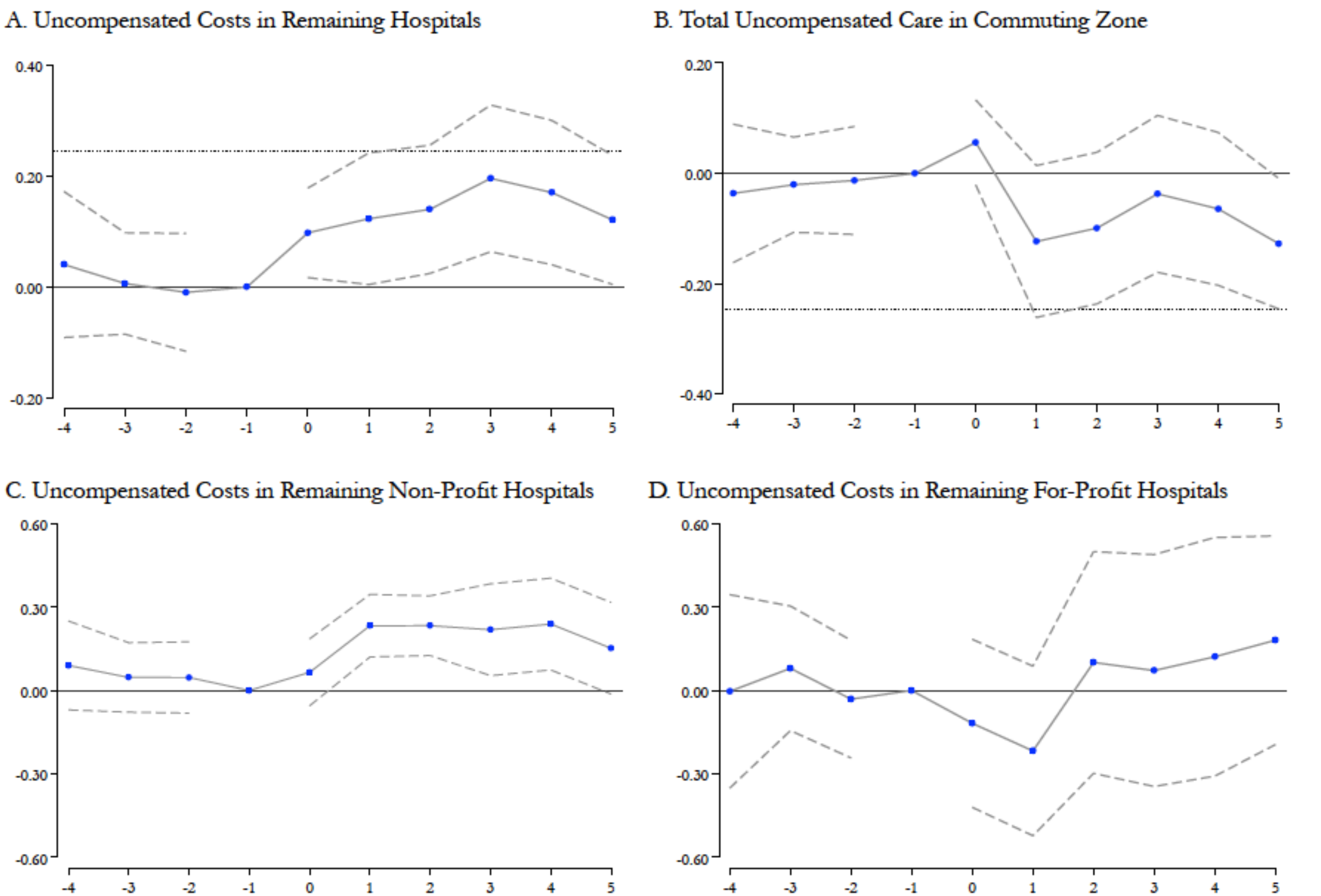
Appendix Figure A11. Change in Number of Hospitals in Commuting Zone After a Hospital Closure



Note: This figure plots point estimates from a regression of number of hospitals in each commuting zone on a series of exhaustive indicator variables for the years since the closure of a large hospital. The year before the closure is the omitted category. The data consist of GAO records of hospital closures combined with the AHA survey. See text for details. The dashed lines connect 95-percent confidence intervals.

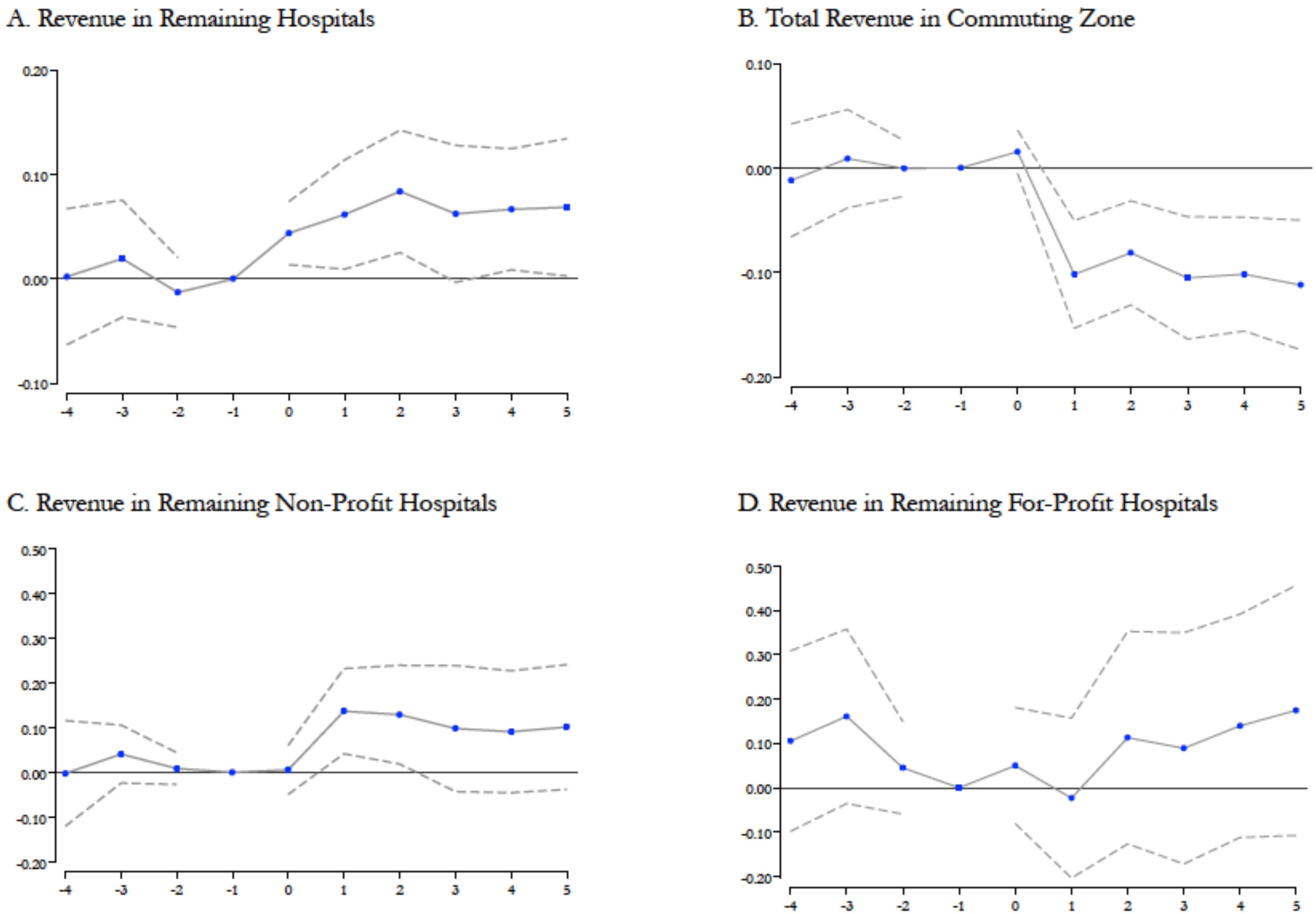
“Hospitals as Insurers of Last Resort” – Additional findings

Figure 8. Change in Uncompensated Care in a Commuting Zone After a Hospital Closure



“Hospitals as Insurers of Last Resort” – Additional findings

Figure 9. Change in Revenue in a Commuting Zone After a Hospital Closure



“Hospitals as Insurers of Last Resort” – Additional findings

Table 5—Effect of Uninsured Population on Profit Margins

Dependent variable: Patient-care profit margin	(1)	(2)	(3)	(4)
Panel A. All hospitals				
Share of population uninsured	–0.089	–0.104	–0.145	–0.160
	(0.062)	(0.058)	(0.067)	(0.068)
	[0.158]	[0.080]	[0.034]	[0.022]
R^2	0.659	0.663	0.707	0.708
Observations	1,224	1,224	1,224	1,224
Panel B. Nonprofit hospitals				
Share of population uninsured	–0.102	–0.108	–0.135	–0.143
	(0.043)	(0.044)	(0.045)	(0.046)
	[0.023]	[0.017]	[0.005]	[0.003]
R^2	0.666	0.667	0.716	0.717
Observations	1,224	1,224	1,224	1,224

"Hospitals as Insurers of Last Resort" – Additional findings

- Following a hospital closure, most of the uncompensated care provided by the closing hospital shows up at nearby hospitals in the same market ("spillover effect")
- **Spillover effects are concentrated in non-profit hospitals (not at for-profit hospitals)**
- Hospital operating profits decrease when the # of uninsured increase in local market [↓ profits is evidence against "cost-shifting" to privately-insured patients]
- Results suggest that state decisions not to expand Medicaid achieve savings for the government at the expense of hospitals and that the **incidence of uncompensated care falls primarily on hospitals**

“Hospitals as Insurers of Last Resort” – Additional findings

*“Memorial officials say they fear that if St. Elizabeth’s moves, their Belleville hospital will be overwhelmed and will **get most of the area’s uninsured and Medicaid patients.**”*

- *The Atlantic,* April 2015

"Hospitals as Insurers of Last Resort" – Additional findings

*"HCA decided **not to treat patients who came in with non-urgent conditions**, like a cold or the flu or even a sprained wrist, unless those **patients paid in advance** … about 1.3 percent, 'chose to seek alternative care options.'"*

- *New York Times*, 2012

*"Led by the Nashville-based HCA, a **growing number of hospitals have implemented the pay-first policy** in an effort to divert patients with routine illnesses from the ER after they undergo a federally required screening."*

- *Washington Post*, 2012

“Hospitals as Insurers of Last Resort” – **political economy**

- Hospital uncompensated care costs may help understand the **political economy** of Medicaid program
- Some economists and political scientists believe that means-tested programs are not politically viable; i.e., “a program for the poor is a poor program” (McElvaine 1984)
- Cash welfare in the U.S. did not survive in the 1990s, and SNAP generosity reduced recently (+ work requirements). **By contrast, Medicaid (absent a few isolated disenrollments) has only grown in size over time**
- We speculate: *“A unique aspect of Medicaid is that it directly benefits not only the citizens it covers, but also the hospitals they visit. Since hospitals are an important political force, the factors requiring hospitals to provide uncompensated care may contribute to Medicaid’s long-term political stability.”*

Outline

- For-profit versus Non-profit hospitals
- Hospitals as Insurers of Last Resort
- The Samaritan's Dilemma
- **Cost-Shifting in Hospitals**

Cost-shifting in hospitals

- Hospital has flexible capacity to serve uninsured patients & privately-insured patients (i.e., no fixed costs, constant marginal costs of $500 for uninsured patients and $2,000 for privately-insured patients)

- 100 patients are uninsured and need to be treated due to EMTALA. They received uncompensated care from the hospital.

- Market demand from privately-insured patients is given by inverse demand: $P = 5000 - Q$

<u>Question:</u> What is the optimal (profit-maximizing) number of privately-insured patients served by hospital?

Cost-shifting in hospitals

Profits for the hospital from serving Q privately-insured patients and N uninsured patients:

$$\max_{Q} \quad Q * (5000 - Q) - 2000 * Q - N * 500$$

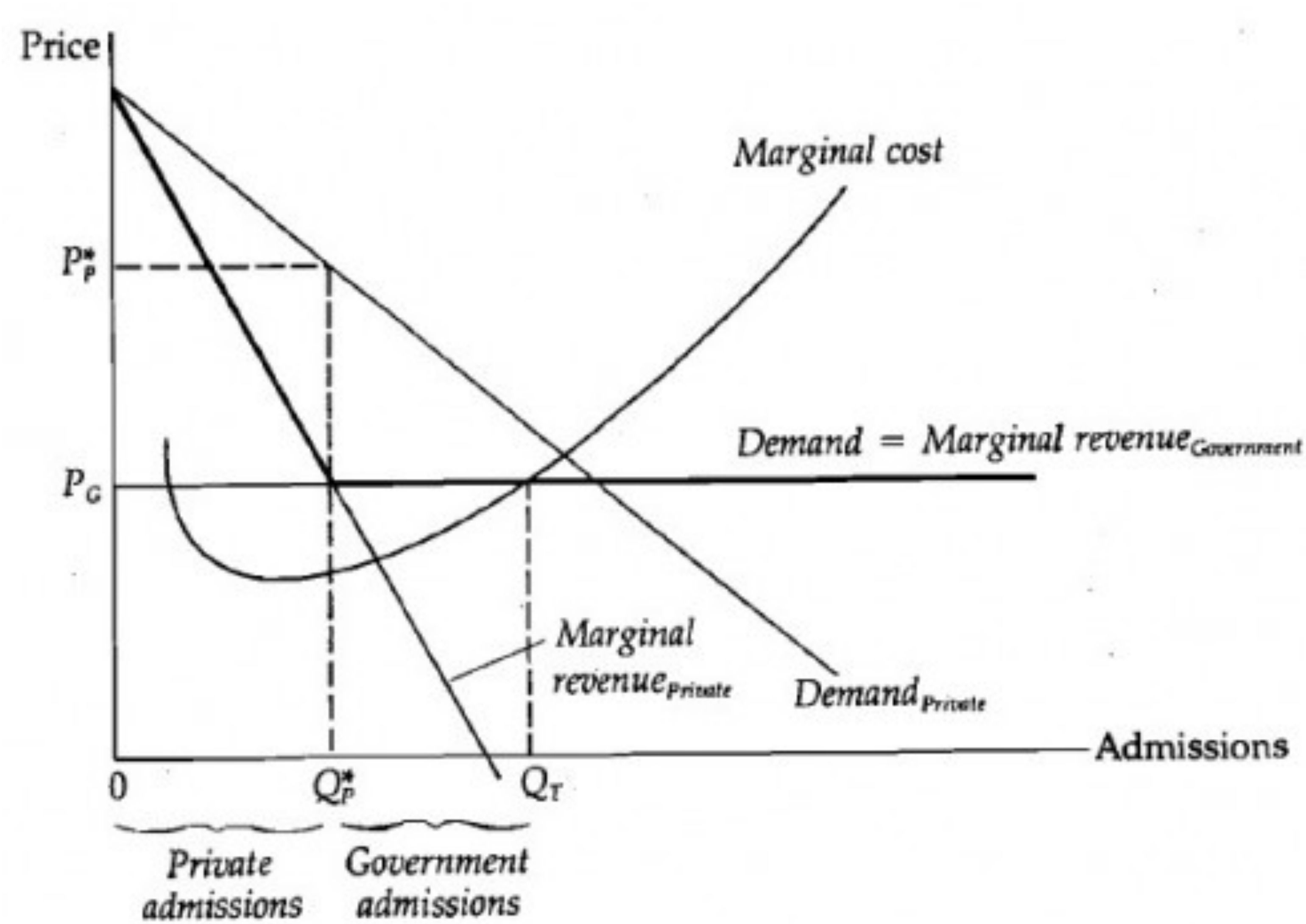
$$\text{MR} = 5000 - 2Q$$

$$\text{MC} = 2000$$

$$Q^* = 1500, \;\; P^* = \$3500$$

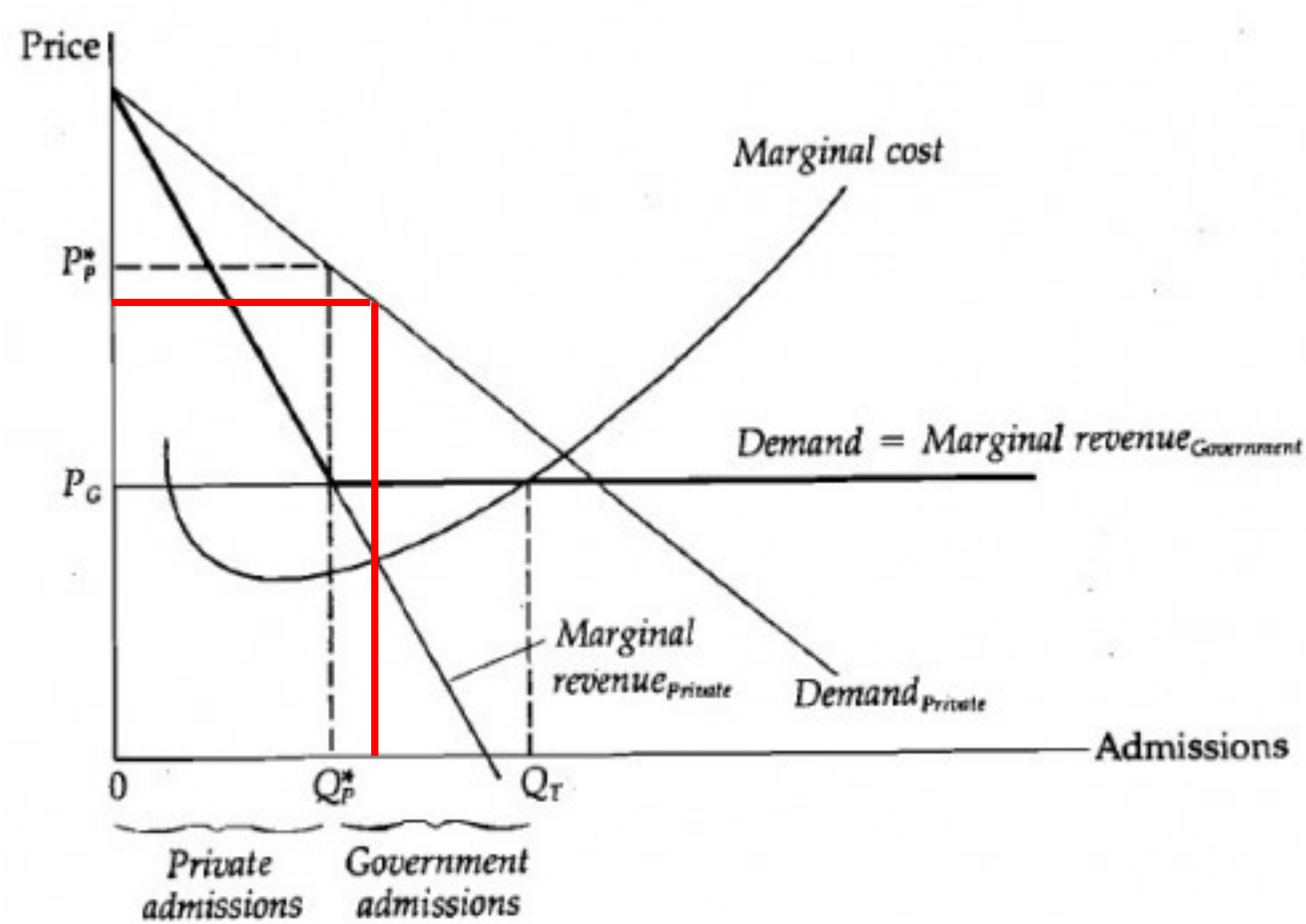
<u>Result:</u> With "separable" uncompensated care costs (e.g., constant marginal costs is sufficient), then there is no cost-shifting from the uninsured to the privately insured

Cost-shifting in hospitals – Medicaid/Medicare payments



Source: theincidentaleconomist.com/wordpress/cost-shifting-theory-under-profit-maximization-part-1/

Cost-shifting in hospitals – Medicaid/Medicare payments



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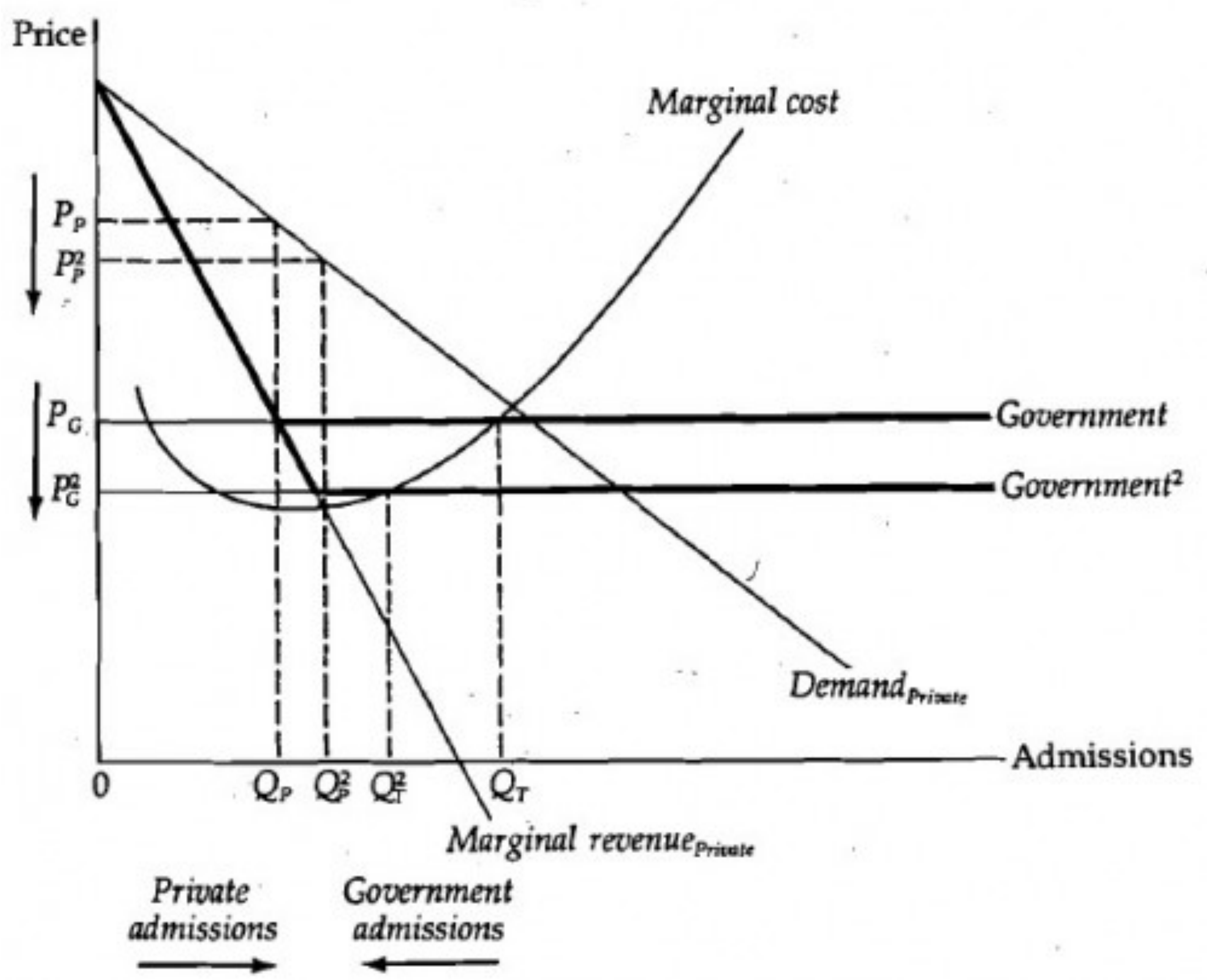
Cost-shifting in hospitals – Medicaid/Medicare payments



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Milbank Q. 2011 Mar; 89(1): 90–130.
doi: 10.1111/j.1468-0009.2011.00621.x

PMCID: PMC3160596
PMID: 21418314

How Much Do Hospitals Cost Shift? A Review of the Evidence

Austin B Frakt

Findings: Most of the analyses and commentary based on descriptive, industrywide hospital payment-to-cost margins by payer provide a false impression that cost shifting is a large and pervasive phenomenon. More careful theoretical and empirical examinations suggest that cost shifting can and has occurred, but usually at a relatively low rate. Margin changes also are strongly influenced by the evolution of hospital and health plan market structures and changes in underlying costs.

Conclusions: Policymakers should view with a degree of skepticism most hospital and insurance industry claims of inevitable, large-scale cost shifting. Although some cost shifting may result from changes in public payment policy, it is just one of many possible effects. Moreover, changes in the balance of market power between hospitals and health care plans also significantly affect private prices. Since they may increase hospitals' market power, provisions of the new health reform law that may encourage greater provider integration and consolidation should be implemented with caution.

Conclusions

- In the U.S., most hospitals are non-profit hospitals
- In some ways, non-profit hospitals behave like “for-profits in disguise”, but there are also many exceptions:
  - DRG-based “upcoding”
  - Length-of-stay responses to Medicare payment change
  - Uncompensated care cost responses to hospital closures
- Uncompensated care may “crowd out” the demand for formal health insurance
- The Samaritan’s Dilemma provides a distinct rationale for insurance mandates
- There is considerable amount of empirical against “cost-shifting” in hospitals, but many hospital executives continue to believe that it occurs (see reading list!)

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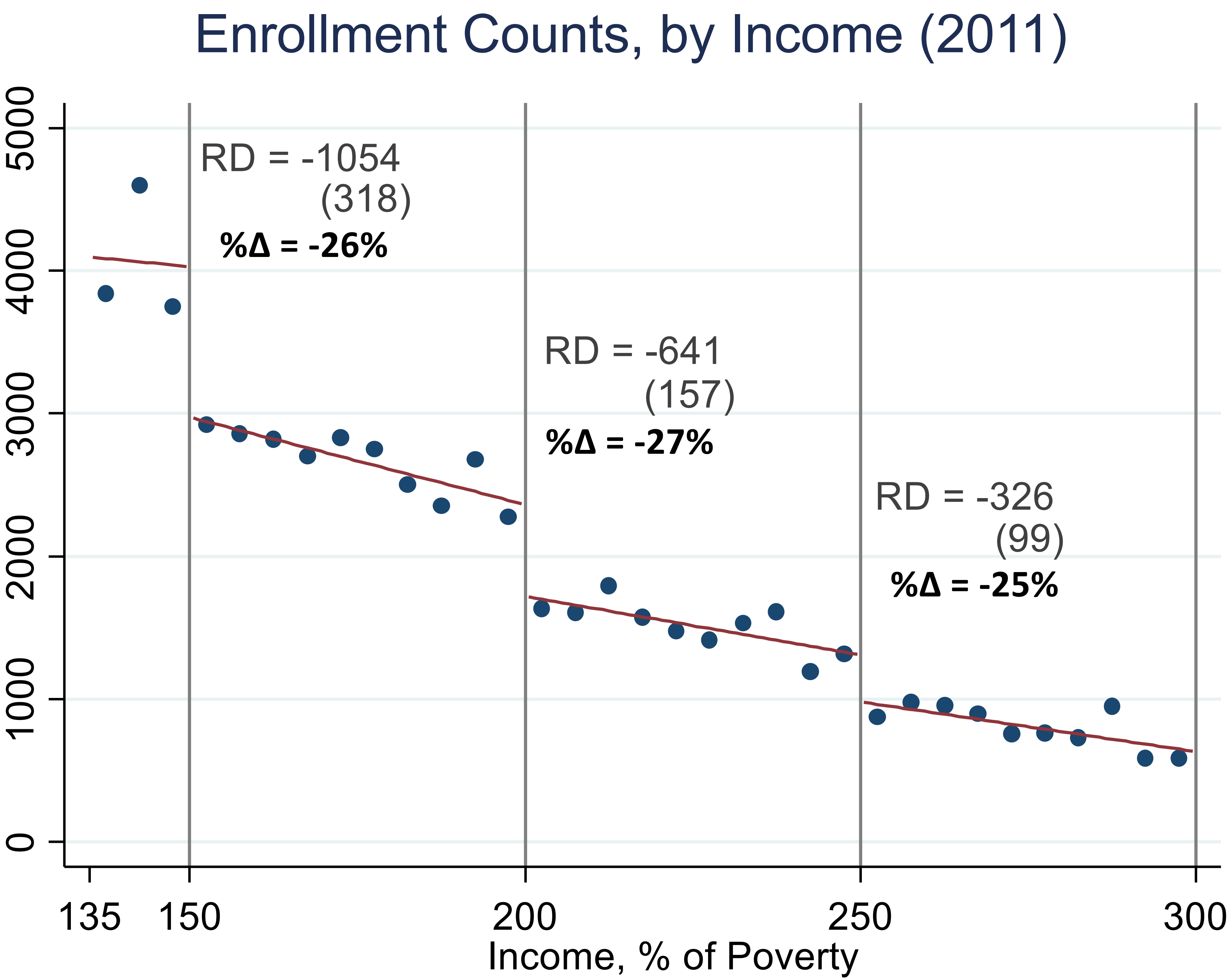
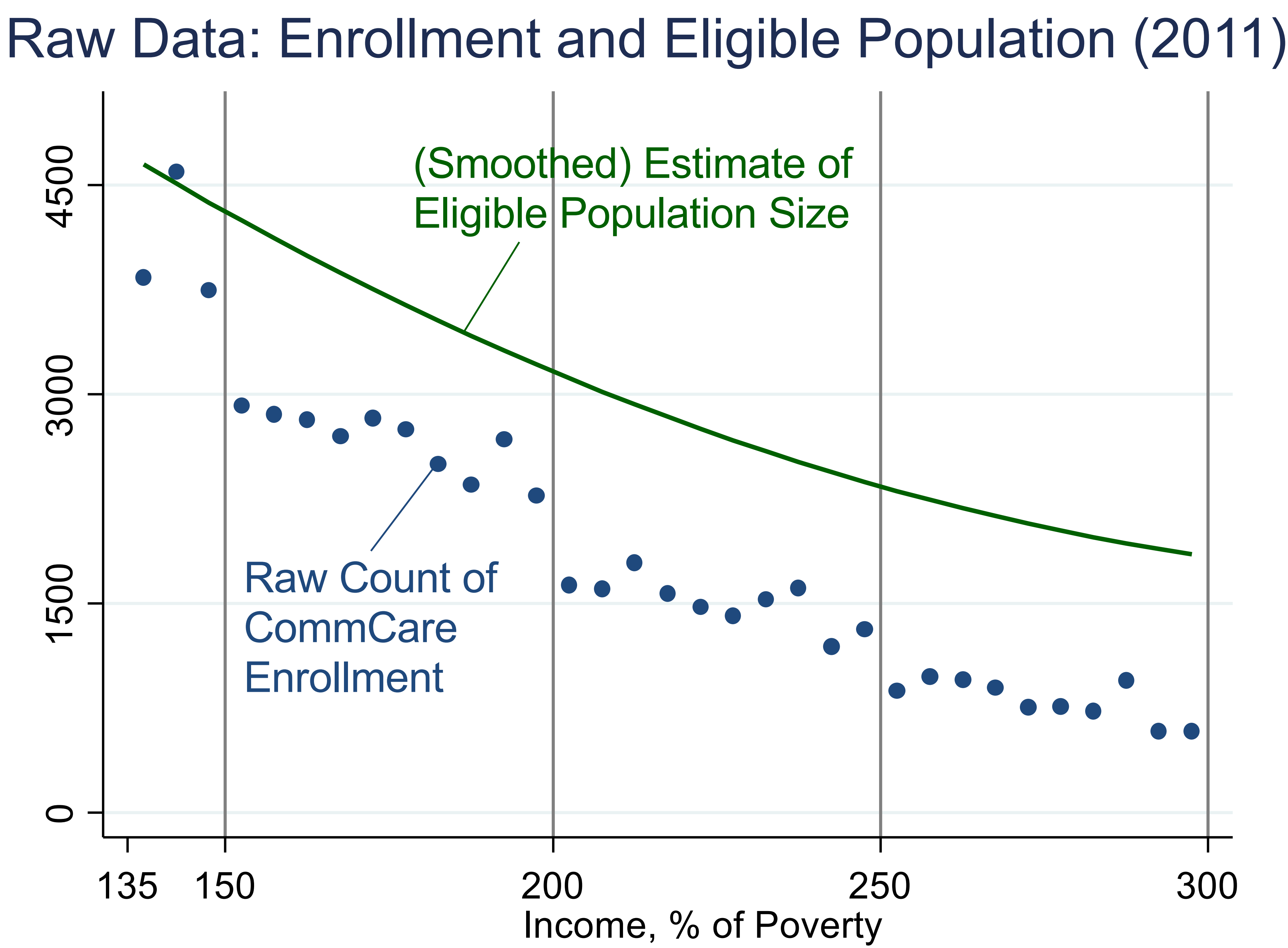
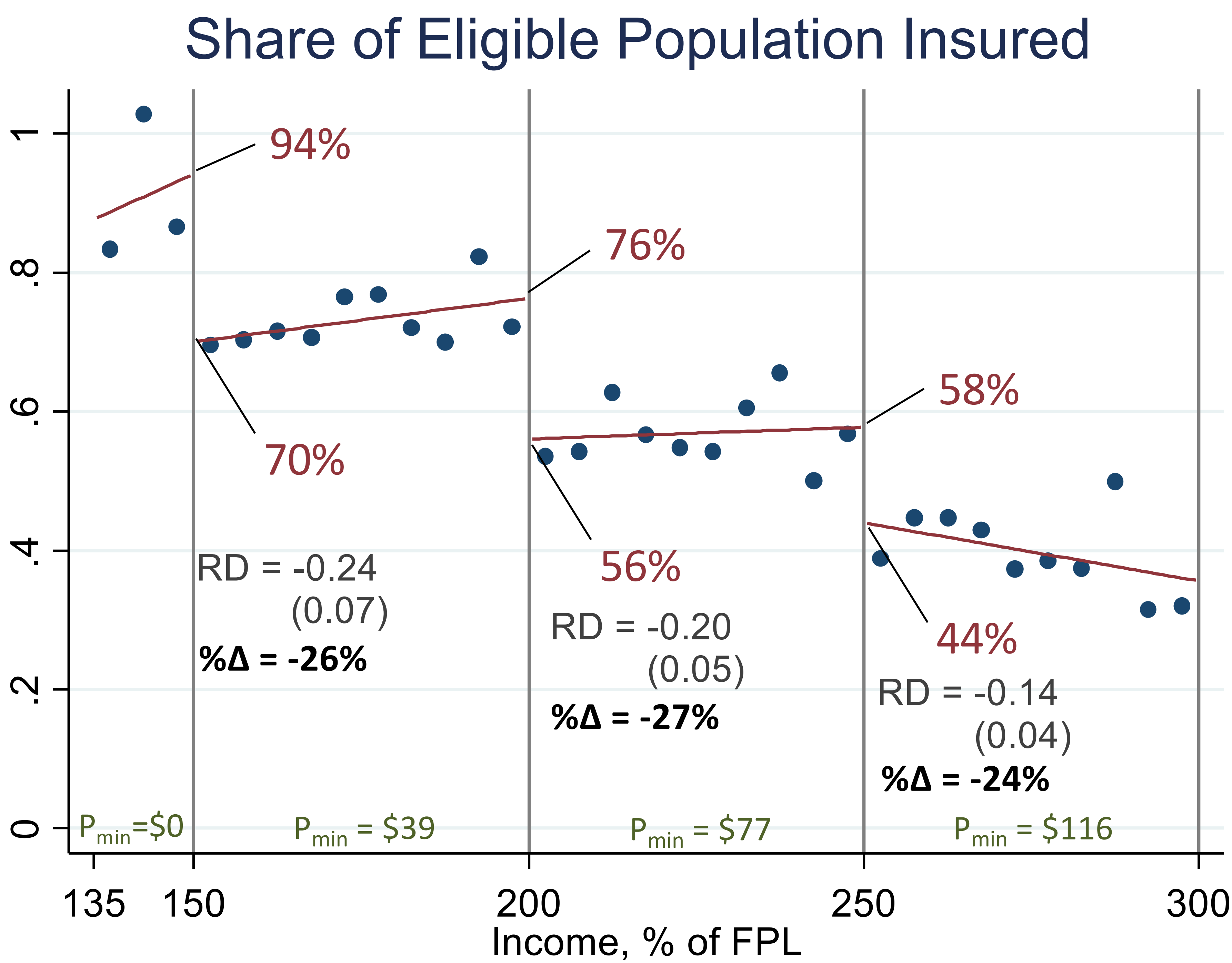
Thanks!

Bonus slides

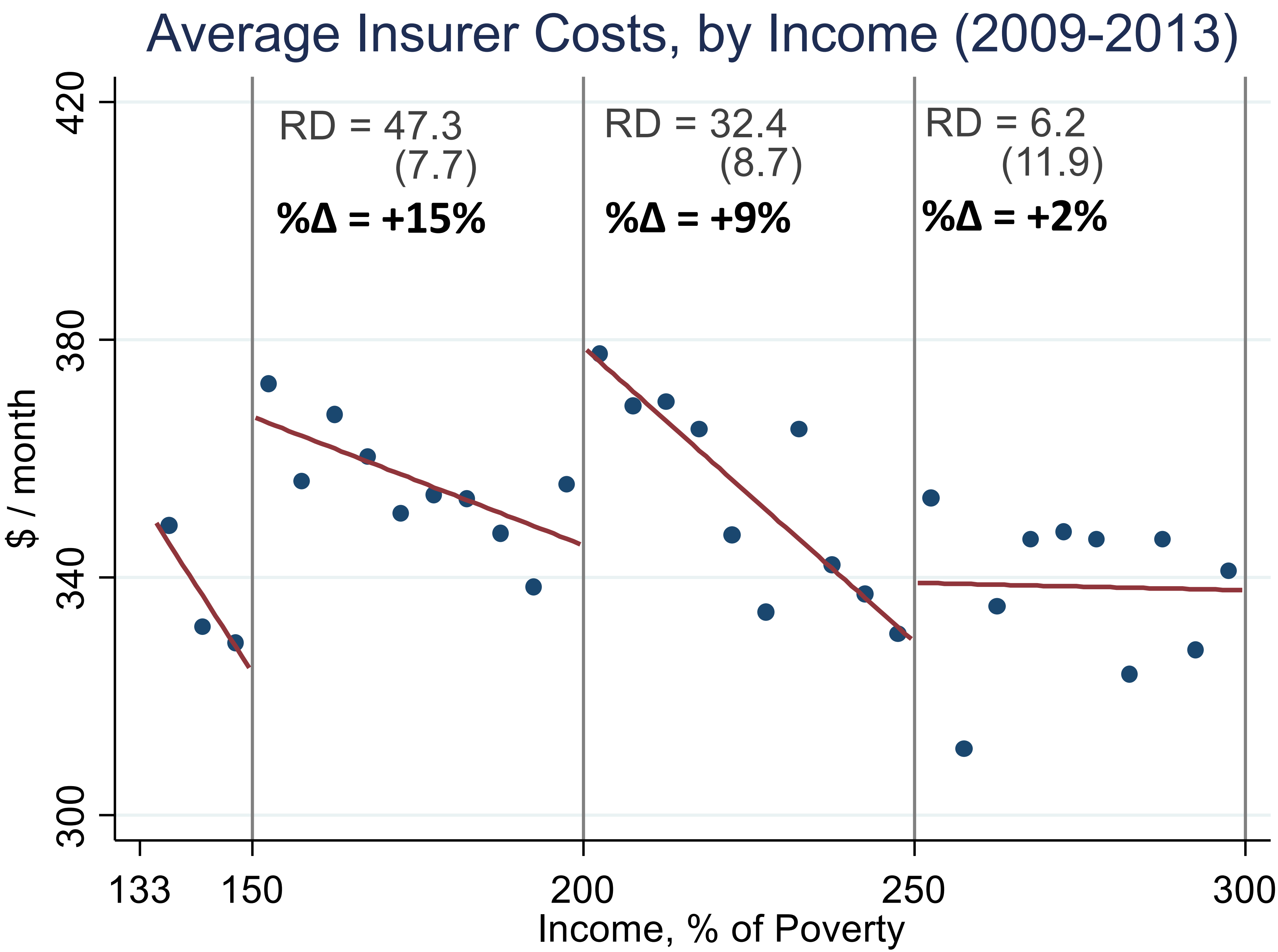


Enrollment Counts, by Income (2011)
RD = -1054
(318)
%Δ = -26%
RD = -641
(157)
%Δ = -27%
RD = -326
(99)
%Δ = -25%
0
1000
2000
3000
4000
5000
135
150
200
250
300
Income, % of Poverty

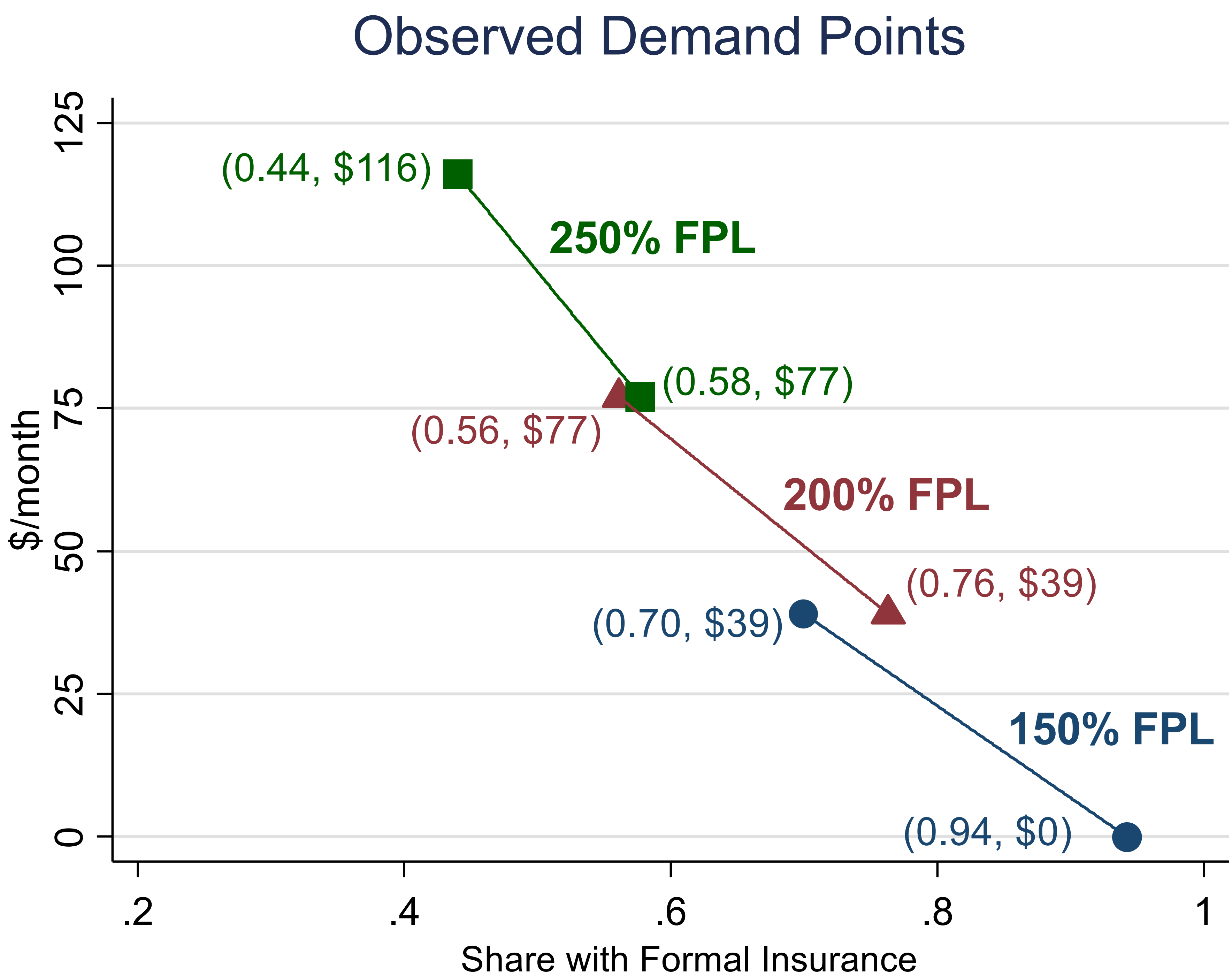

Raw Data: Enrollment and Eligible Population (2011)
(Smoothed) Estimate of Eligible Population Size
Raw Count of CommCare Enrollment
4500
3000
1500
0
135
150
200
250
300
Income, % of Poverty

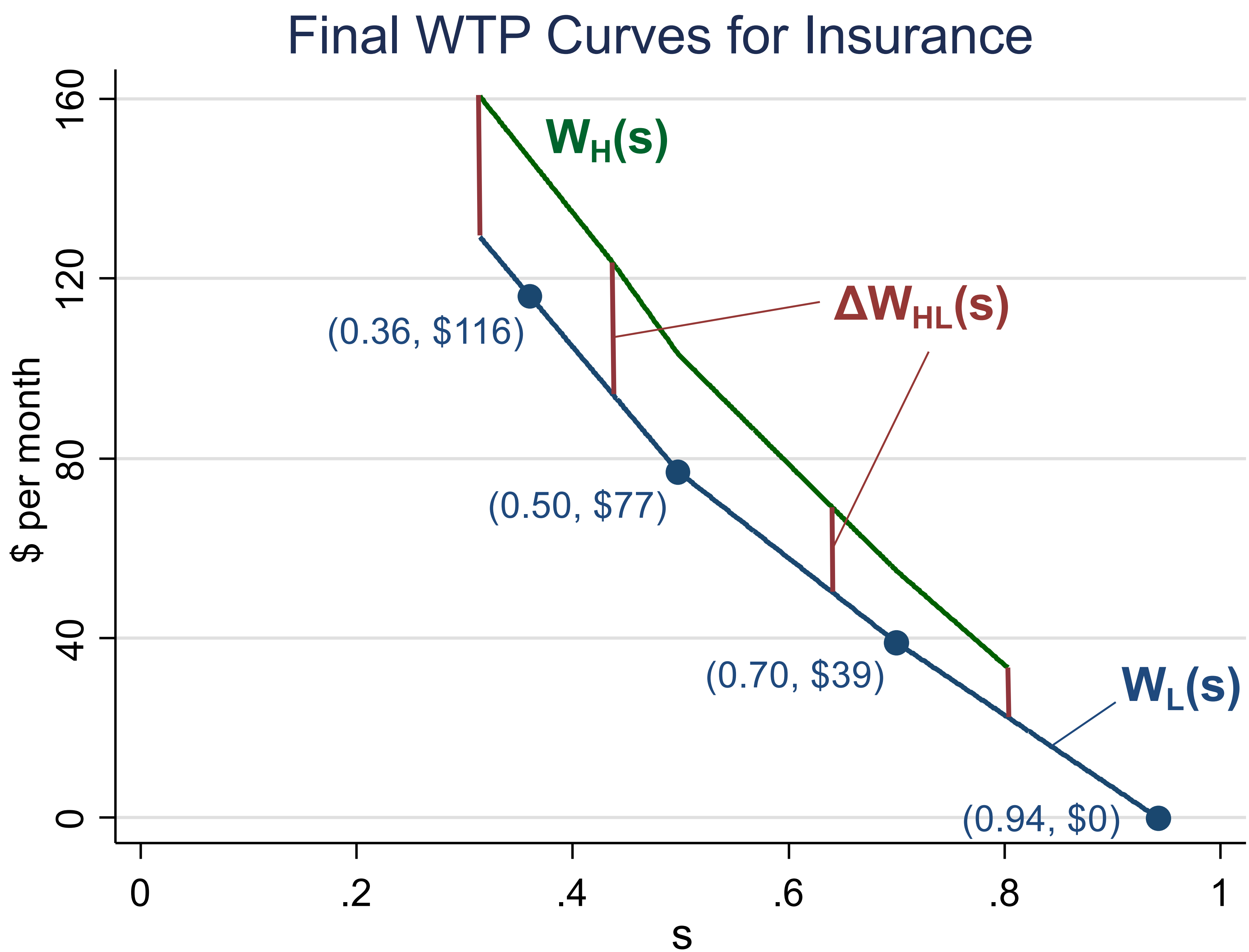


Share of Eligible Population Insured
94%
76%
70%
58%
56%
44%
RD = -0.24
(0.07)
%Δ = -26%
RD = -0.20
(0.05)
%Δ = -27%
RD = -0.14
(0.04)
%Δ = -24%
Pmin=$0
Pmin = $39
Pmin = $77
Pmin = $116
0
.2
.4
.6
.8
1
135
150
200
250
300
Income, % of FPL

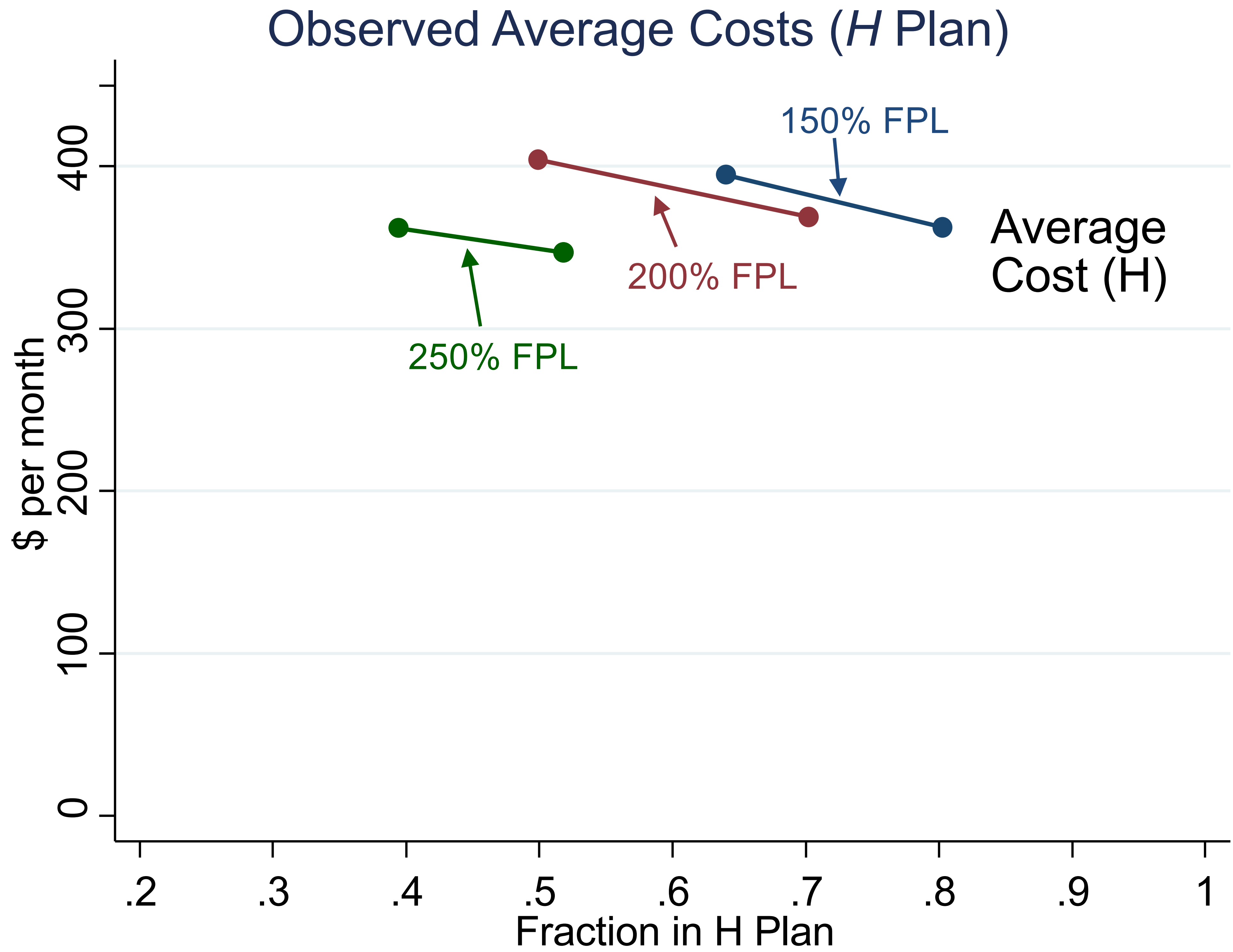


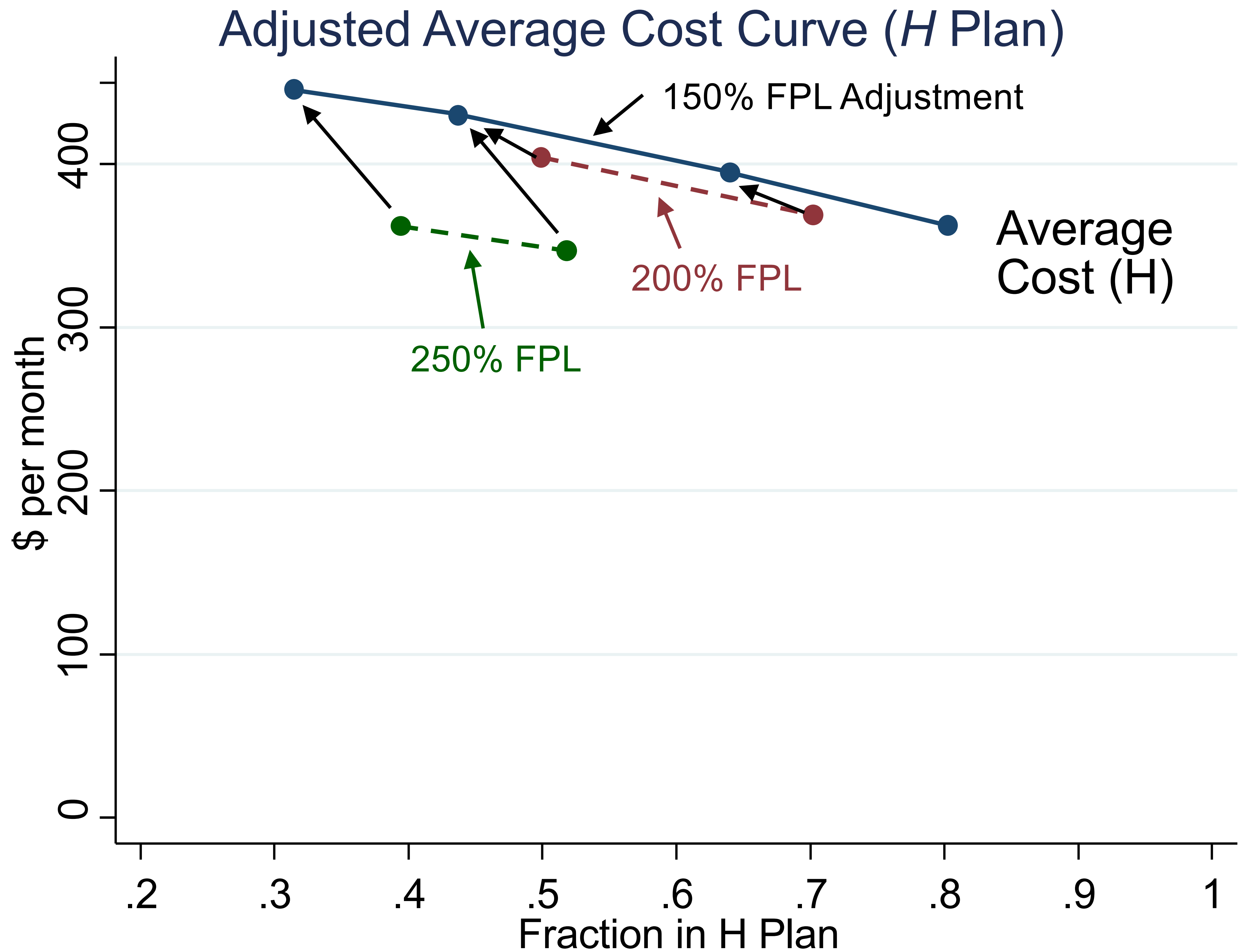
Average Insurer Costs, by Income (2009-2013)
RD = 47.3
(7.7)
%Δ = +15%
RD = 32.4
(8.7)
%Δ = +9%
RD = 6.2
(11.9)
%Δ = +2%
$ / month
420
380
340
300
133
150
200
250
300
Income, % of Poverty

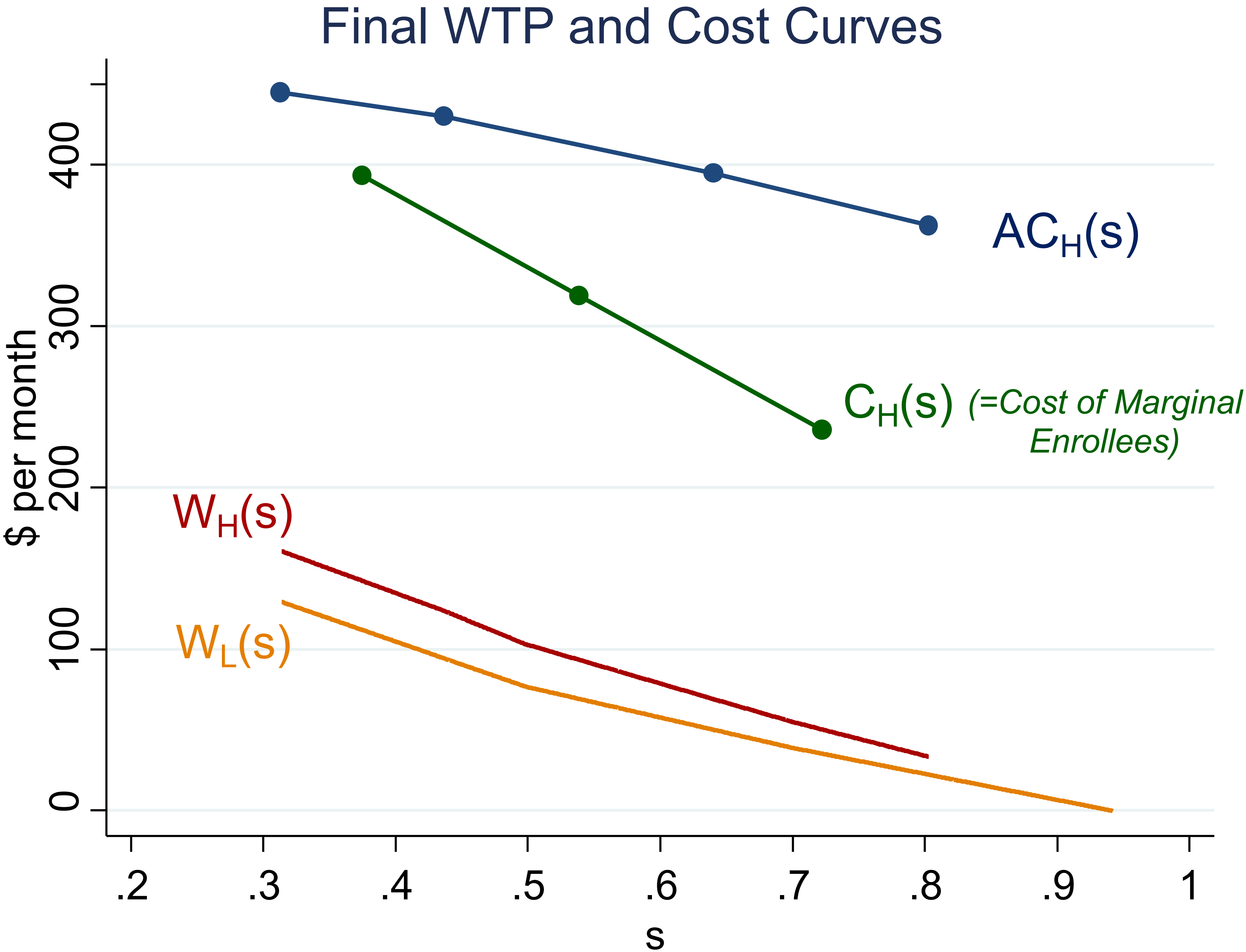

Observed Demand Points
$/month
125
100
75
50
25
0
.2
.4
.6
.8
1
Share with Formal Insurance
(0.44, $116)
250% FPL
(0.58, $77)
(0.56, $77)
200% FPL
(0.76, $39)
(0.70, $39)
150% FPL
(0.94, $0)



Final WTP Curves for Insurance
$ per month
0
40
80
120
160
0
.2
.4
.6
.8
1
s
W_H(s)
ΔW_HL(s)
W_L(s)
(0.36, $116)
(0.50, $77)
(0.70, $39)
(0.94, $0)

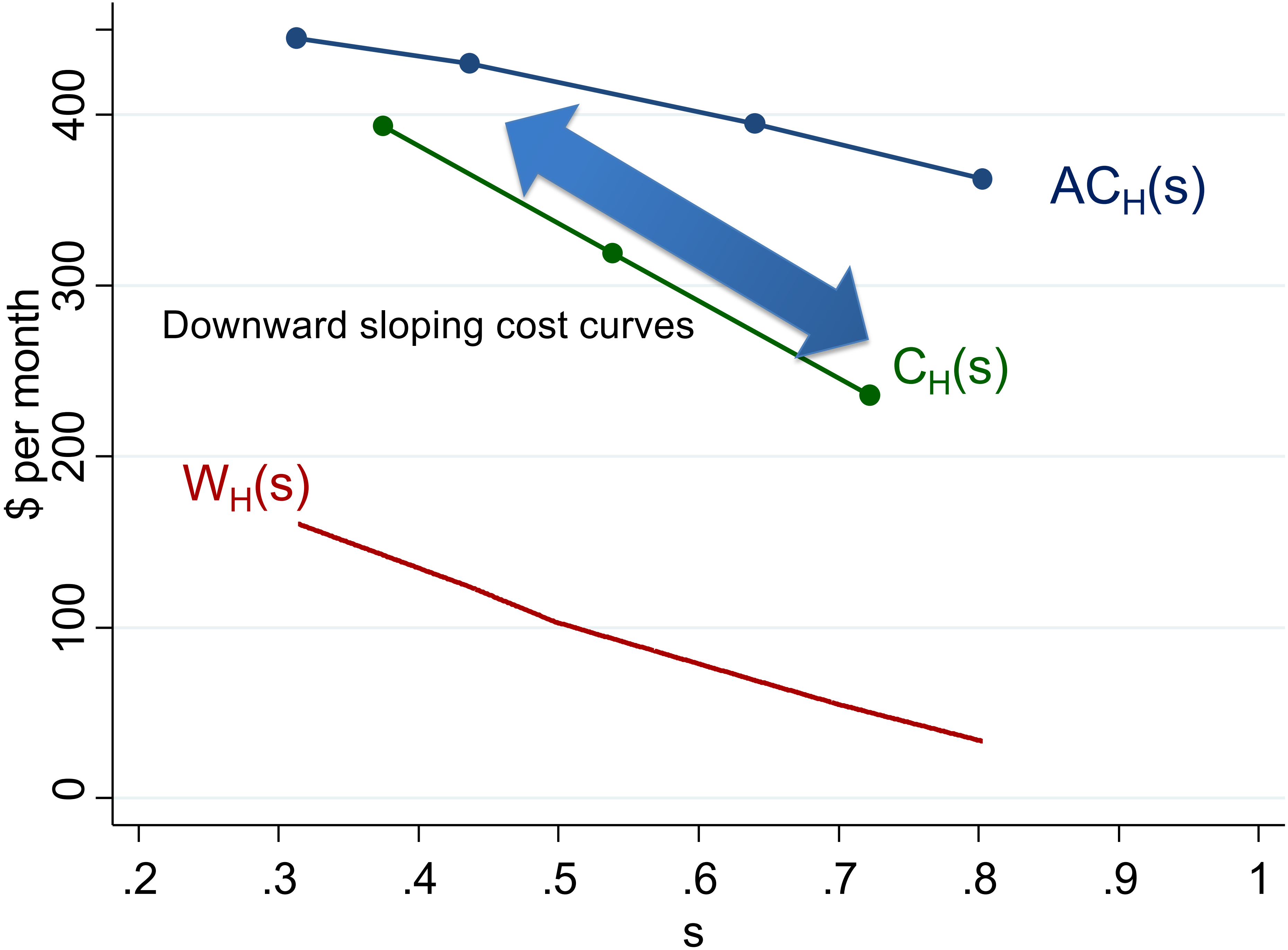

Observed Average Costs (*H* Plan)
150% FPL
200% FPL
250% FPL
Average Cost (H)
$ per month
0
100
200
300
400
.2
.3
.4
.5
.6
.7
.8
.9
1
Fraction in H Plan


Adjusted Average Cost Curve (*H* Plan)
150% FPL Adjustment
Average Cost (H)
200% FPL
250% FPL
$ per month
0
100
200
300
400
.2
.3
.4
.5
.6
.7
.8
.9
1
Fraction in H Plan

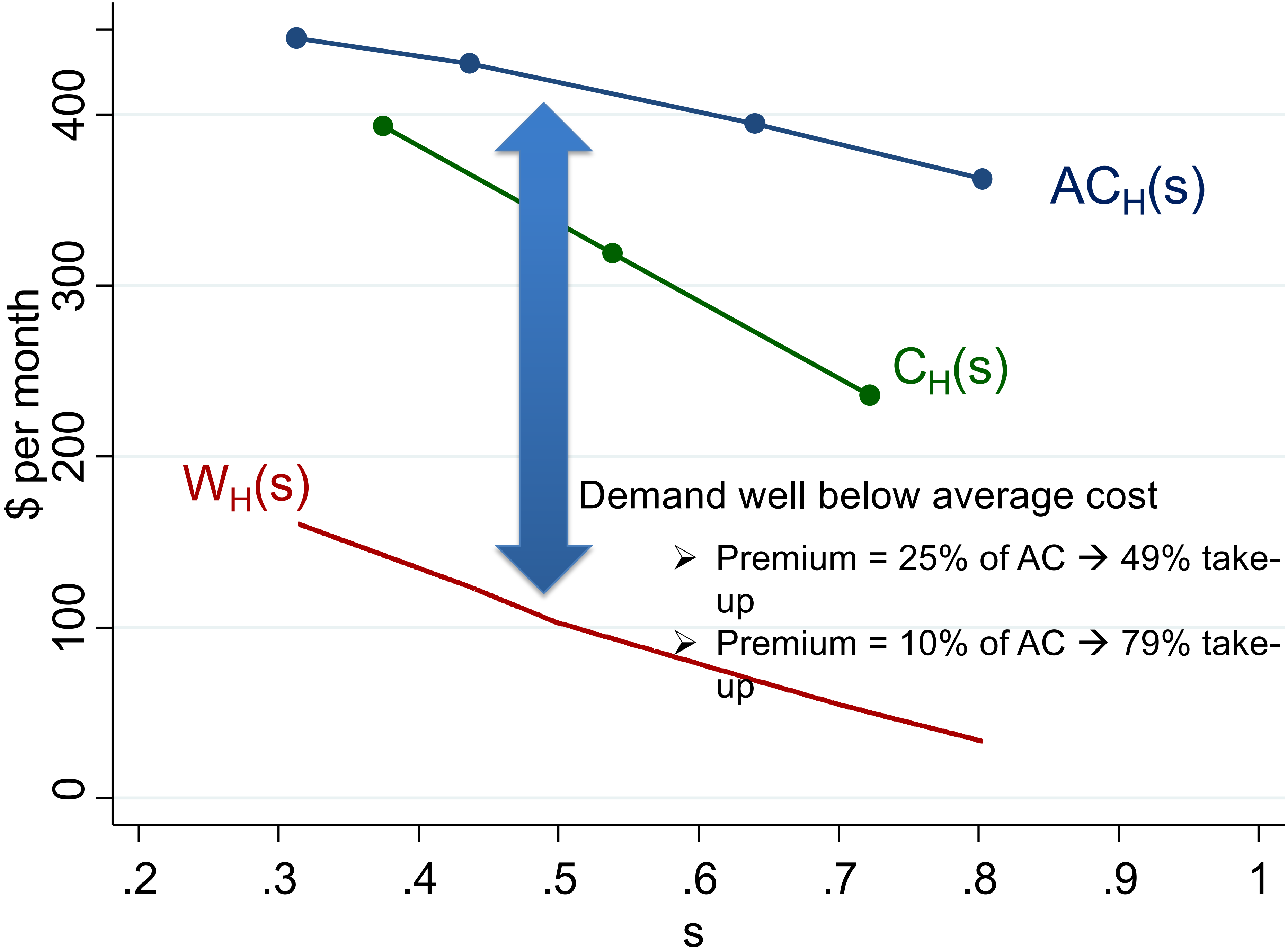


Final WTP and Cost Curves
$ per month
0
100
200
300
400
.2
.3
.4
.5
.6
.7
.8
.9
1
s
$AC_H(s)$
$C_H(s)$ (=Cost of Marginal Enrollees)
$W_H(s)$
$W_L(s)$

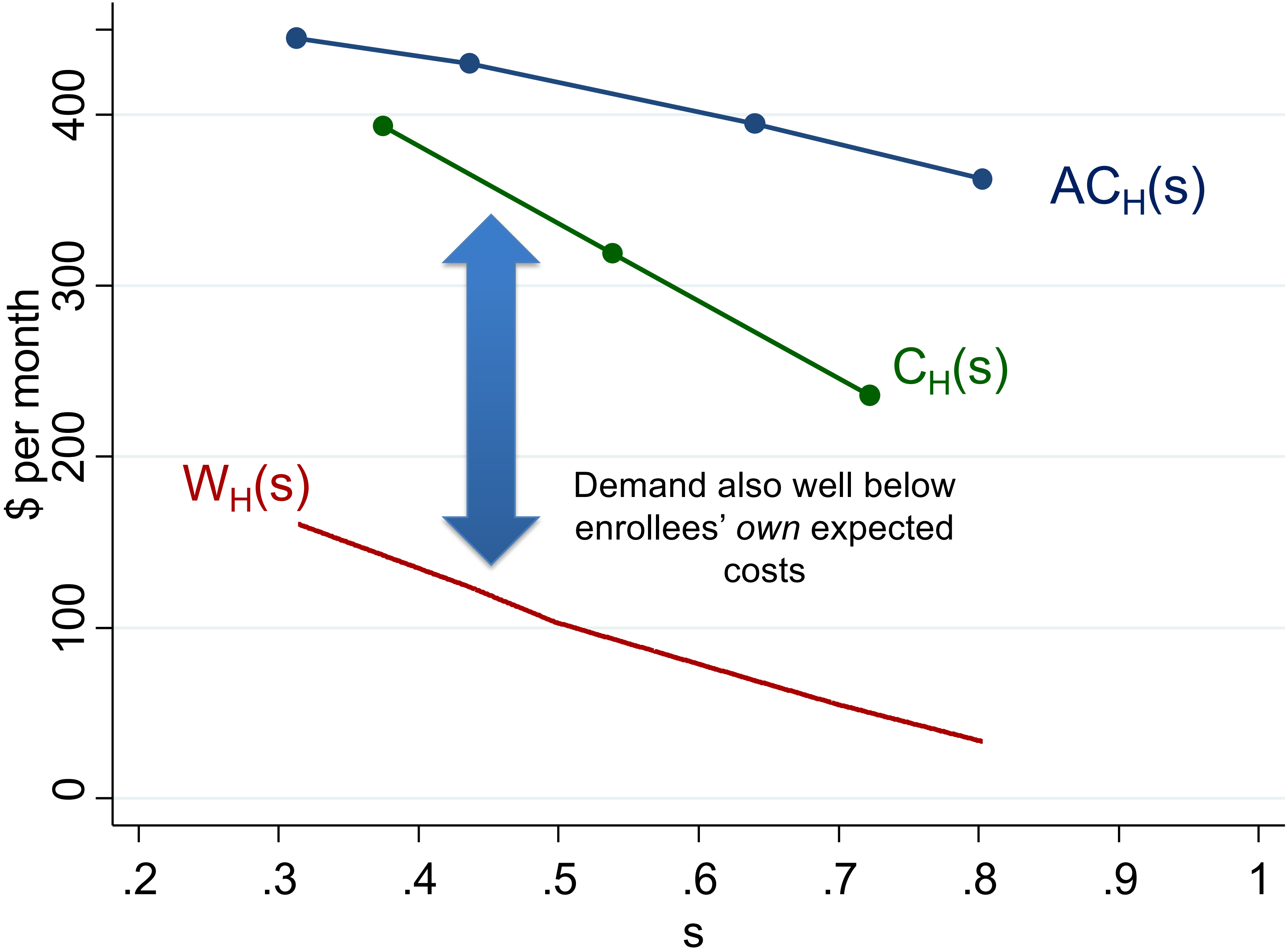
Result #1: Substantial Adverse Selection

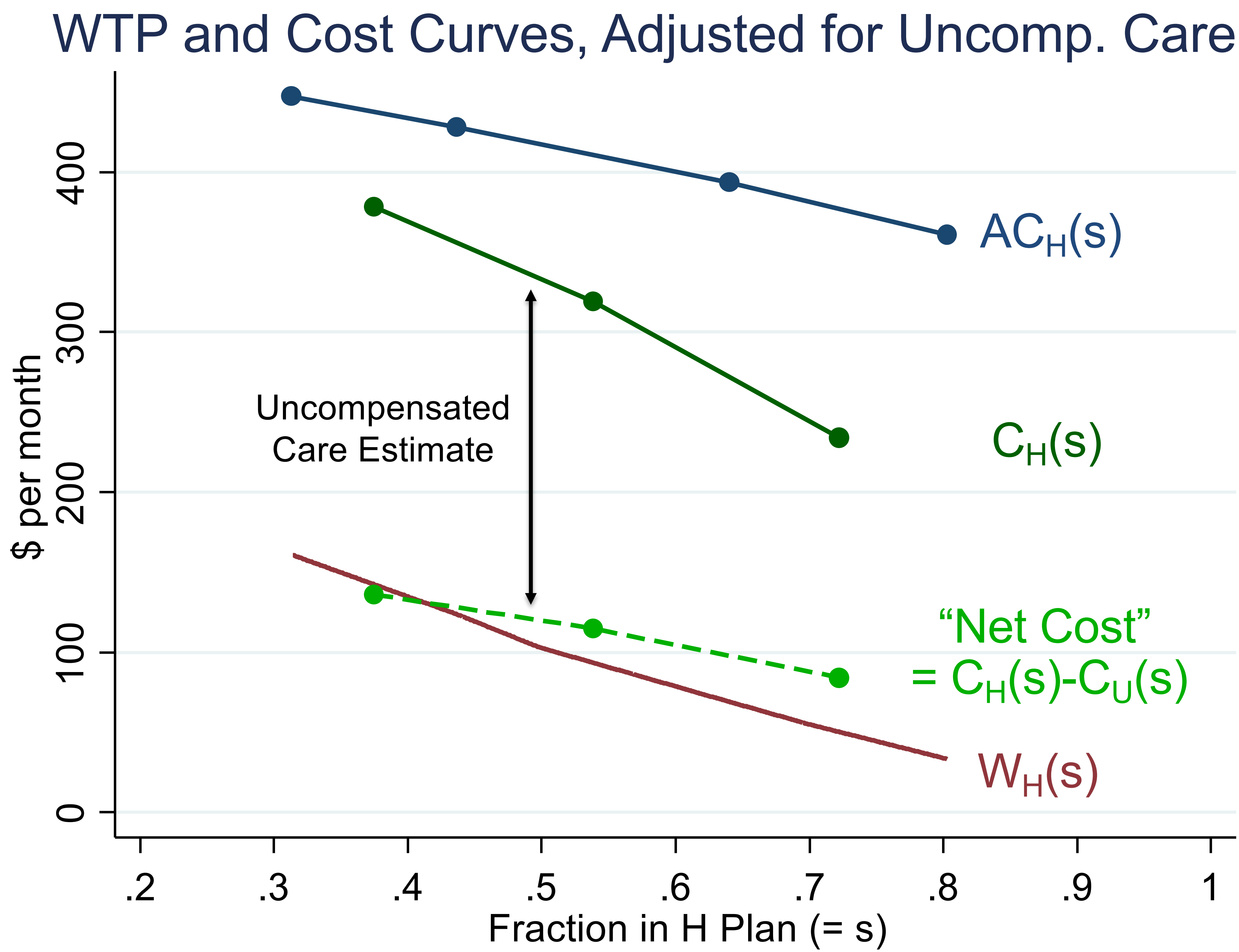


Result #2: Little Take-up w/out Large Subsidies



Result #3: Adverse selection alone cannot explain low coverage





WTP and Cost Curves, Adjusted for Uncomp. Care
$ per month
0
100
200
300
400
.2
.3
.4
.5
.6
.7
.8
.9
1
Fraction in H Plan (= s)
$AC_H(s)$
$C_H(s)$
Uncompensated
Care Estimate
"Net Cost"
$= C_H(s)-C_U(s)$
$W_H(s)$

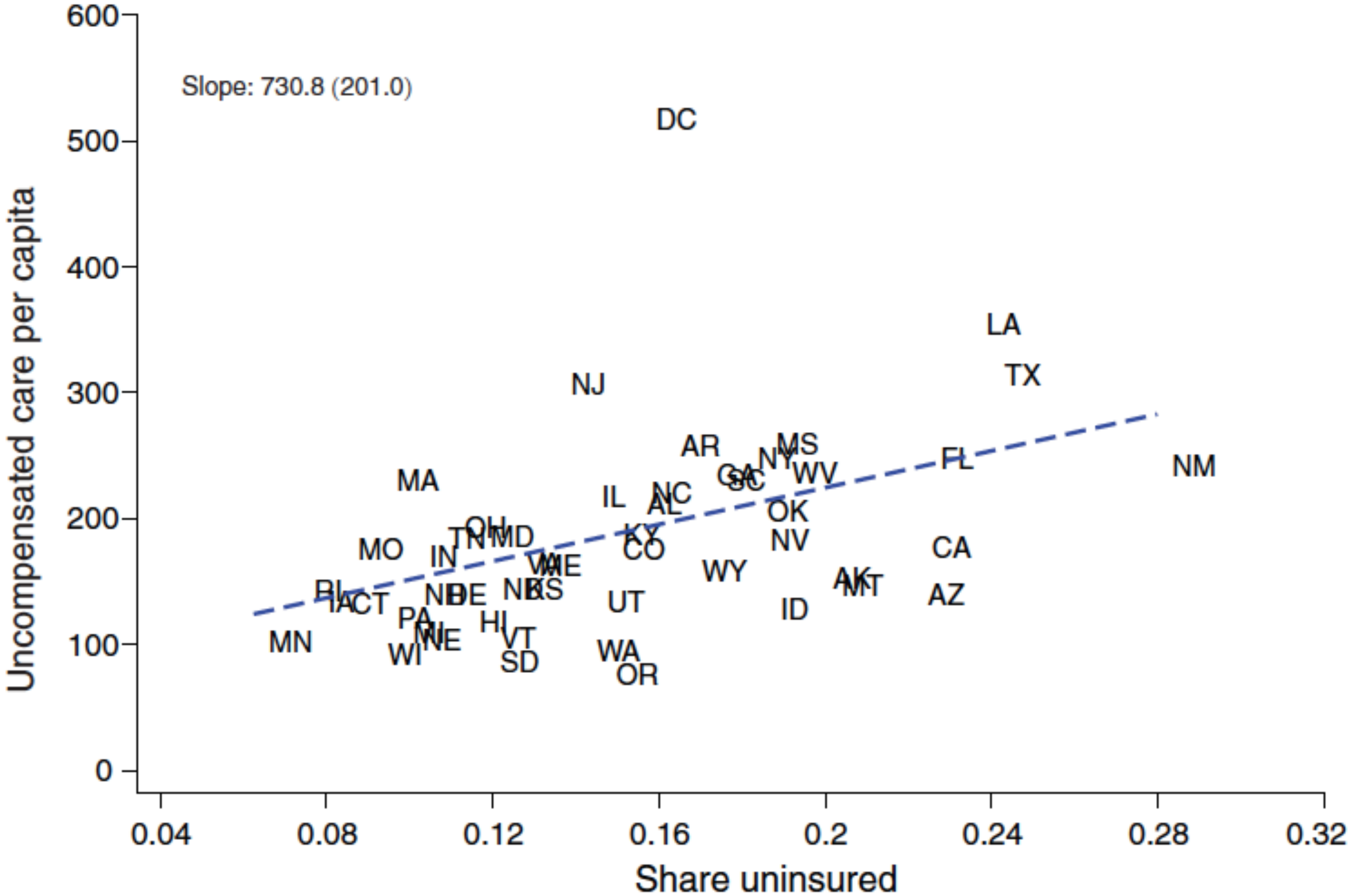
Gartwaite et al. AEJ-Applied: Data

- Data use agreement with AHA to use previously confidential hospital-level financial data from 1984-2011
  - Uncompensated care charges for every AHA hospital
  - Adjust charges using hospital-specific cost-to-charge ratio
  - Adjust all financial outcomes to 2011 dollars

- AHA survey also includes rich financial and non-financial data (e.g., revenue, expenditures, admissions, beds, etc.)

- Use March CPS to determine the insurance status and for socioeconomic covariates

Panel A. 2000 cross section



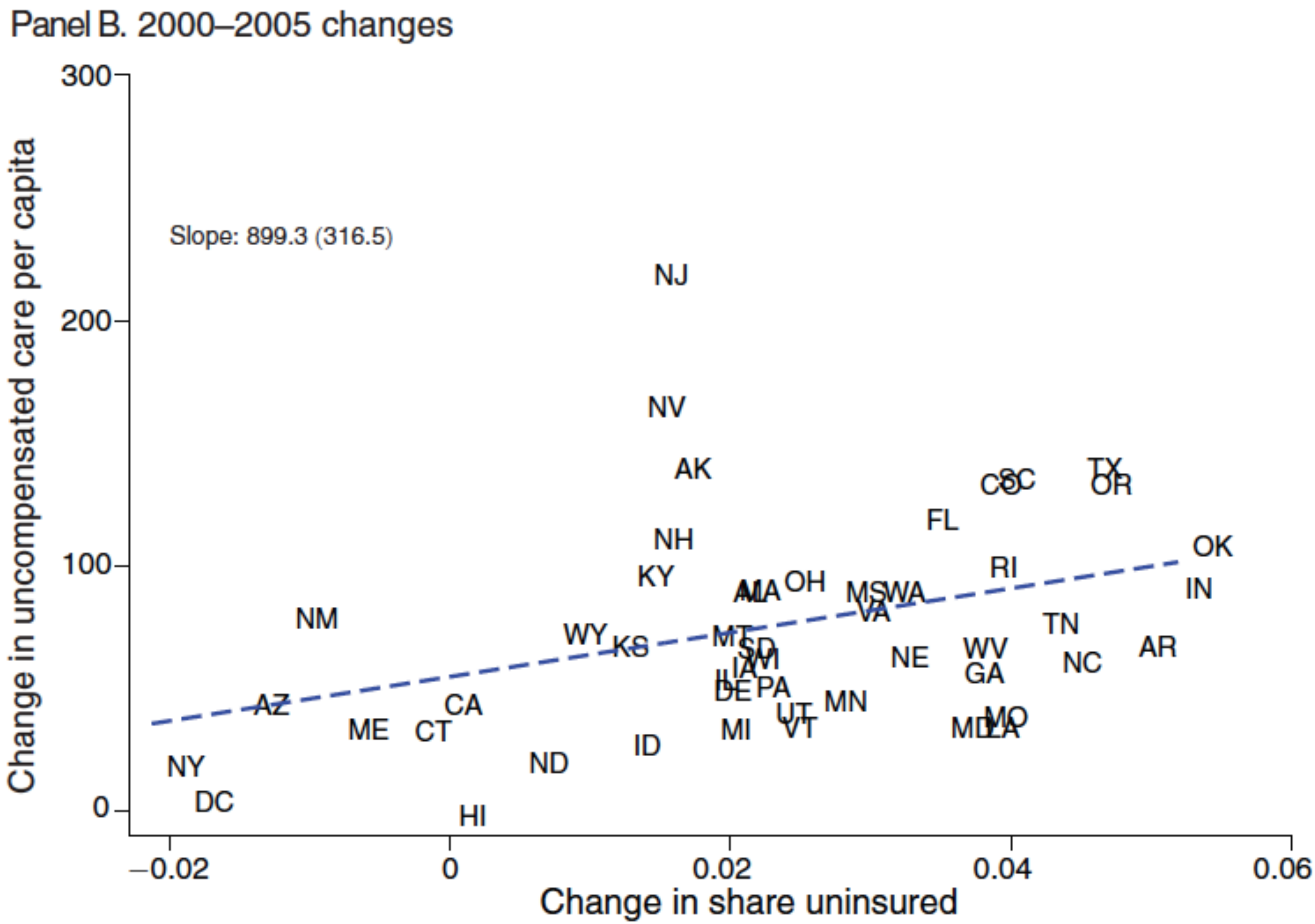


Figure 1. Share Uninsured and Uncompensated-Care Costs

Dependent variable	Per capita uncompensated care			
	(1)	(2)	(3)	(4)
Panel A. All hospitals				
Share of population uninsured	793.37	814.14	841.77	830.51
	(299.71)	(295.10)	(335.49)	(302.37)
	[0.01]	[0.01]	[0.02]	[0.01]
R^2	0.870	0.872	0.889	0.892
Observations	1,224	1,224	1,224	1,224
Panel B. Hospitals with an ED				
Share of population uninsured	797.34	816.90	845.59	832.43
	(308.06)	(304.26)	(349.55)	(315.75)
	[0.01]	[0.01]	[0.02]	[0.01]
R^2	0.864	0.866	0.884	0.887
Observations	1,224	1,224	1,224	1,224
Panel C. Hospitals without an ED				
Share of population uninsured	–4.21	–3.10	–5.04	–3.21
	(11.14)	(11.93)	(17.84)	(17.65)
	[0.71]	[0.80]	[0.78]	[0.86]
R^2	0.480	0.480	0.549	0.551
Observations	1,200	1,200	1,200	1,200

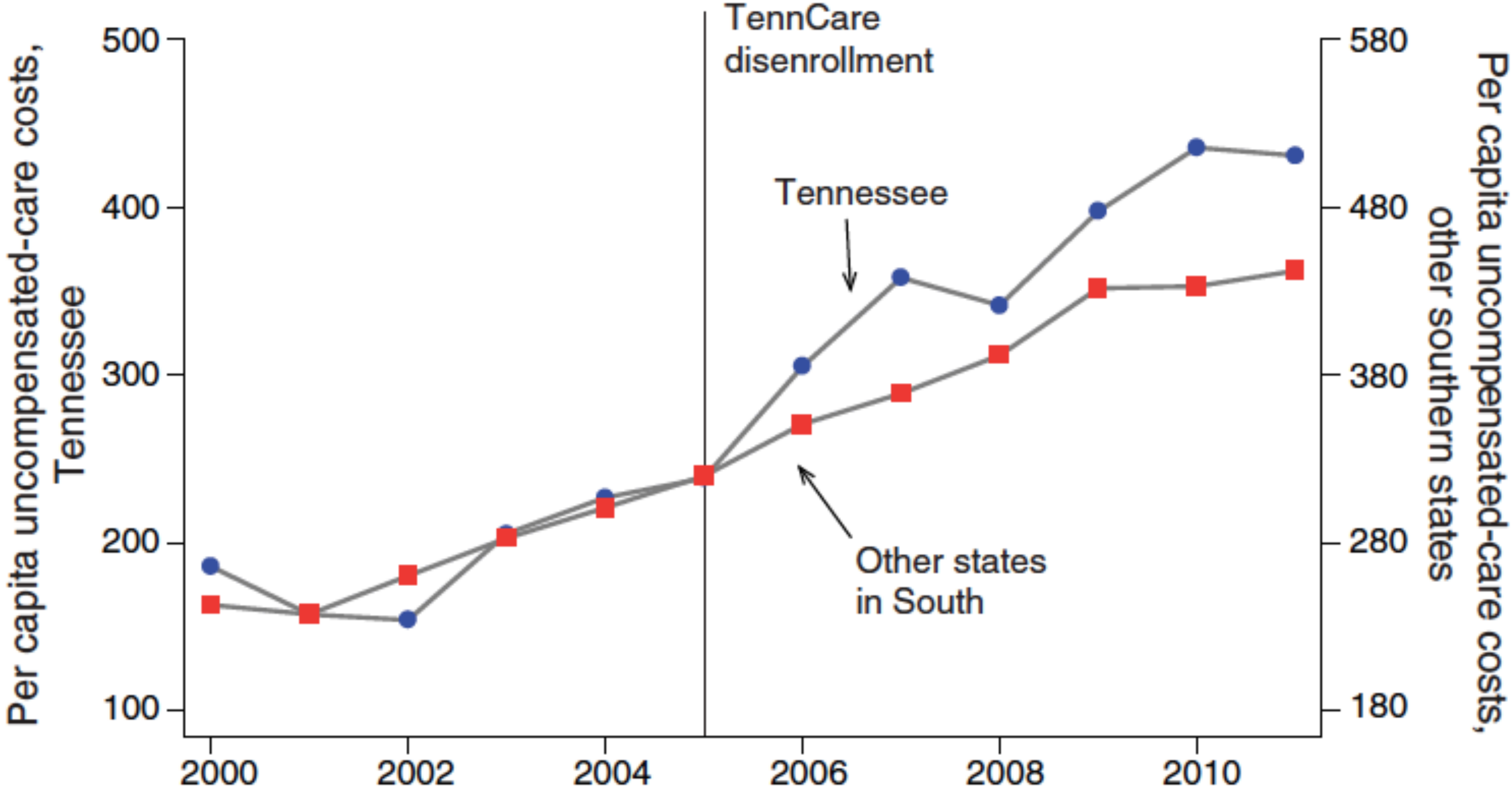
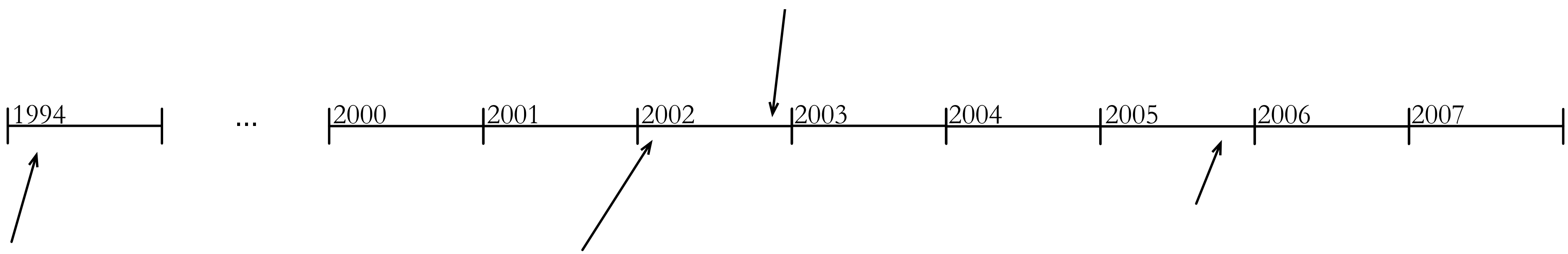


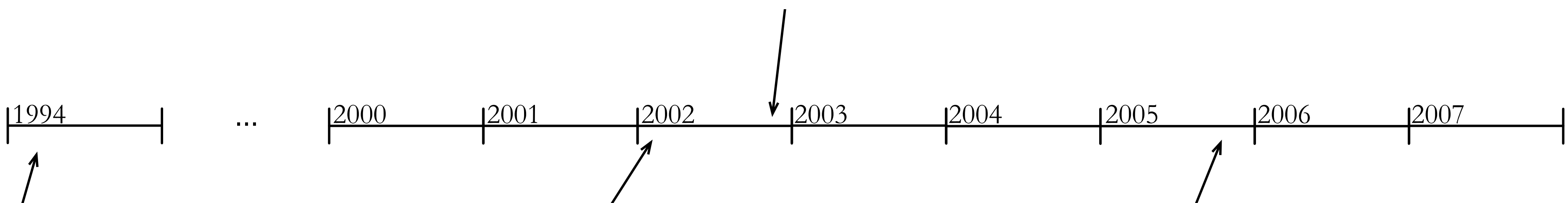
FIGURE 3. UNCOMPENSATED-CARE COSTS IN TENNESSEE



Tennessee creates expansion program for "uninsured" and "uninsurable."

“[e]verybody in the state of Tennessee knows somebody on TennCare they don’t think should be on TennCare. **It needs to be the bronze package, not the platinum package.”**

- Governor Phil Bredesen (D-TN), 2002



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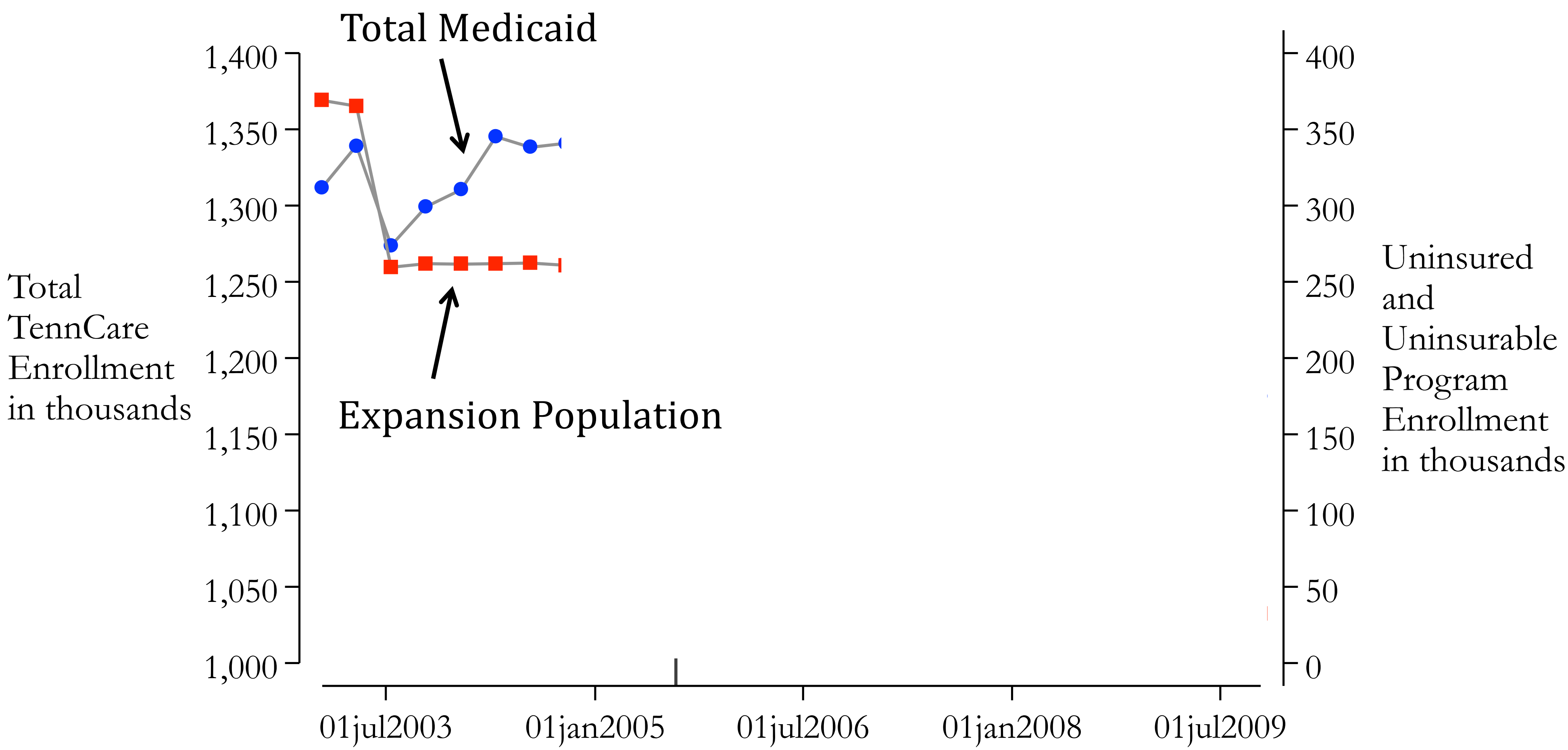
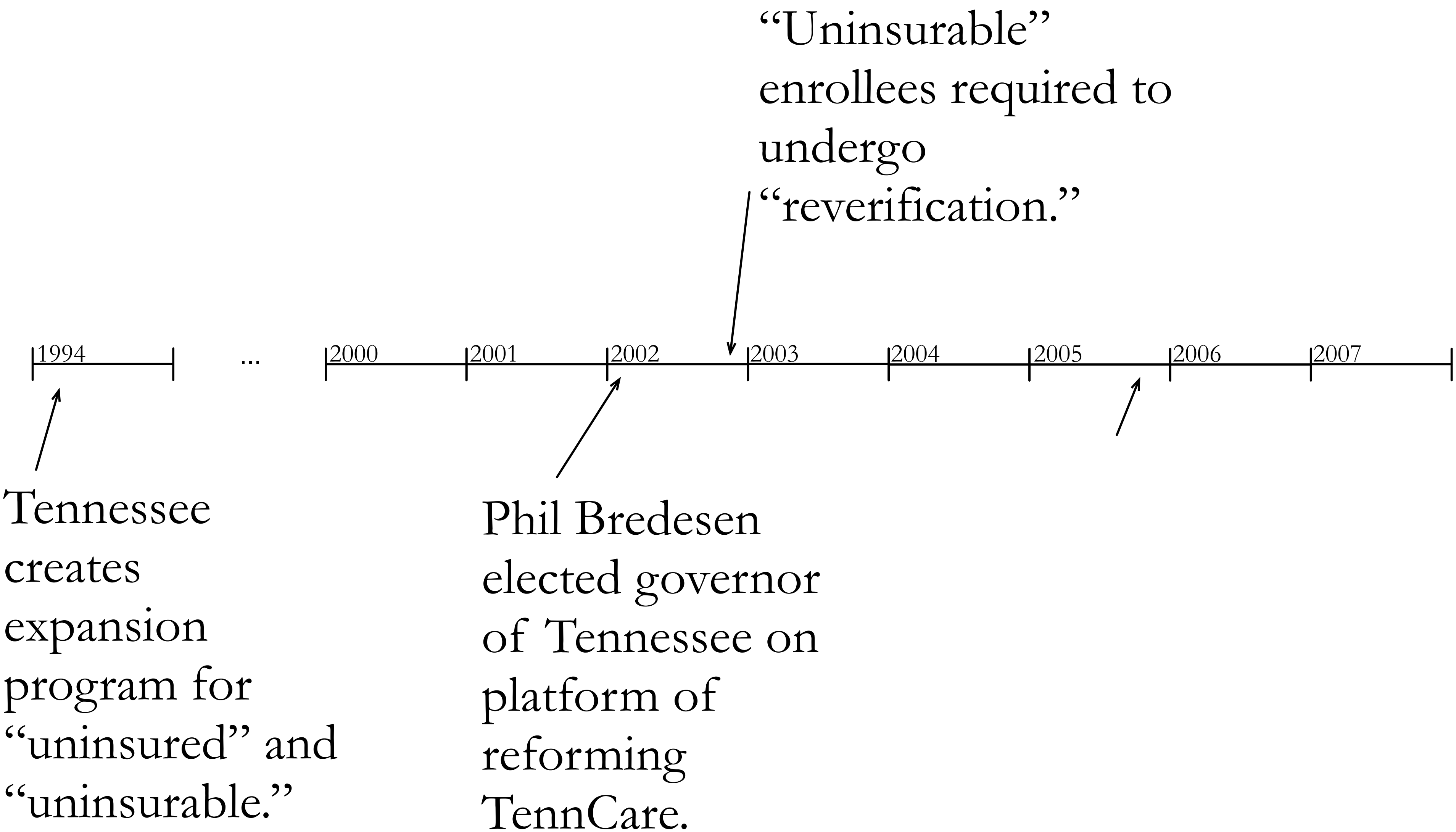
TennCare Population by Category





"Uninsurable" enrollees required to undergo "reverification."
1994
...
2000
2001
2002
2003
2004
2005
2006
2007
Tennessee creates expansion program for "uninsured" and "uninsurable."
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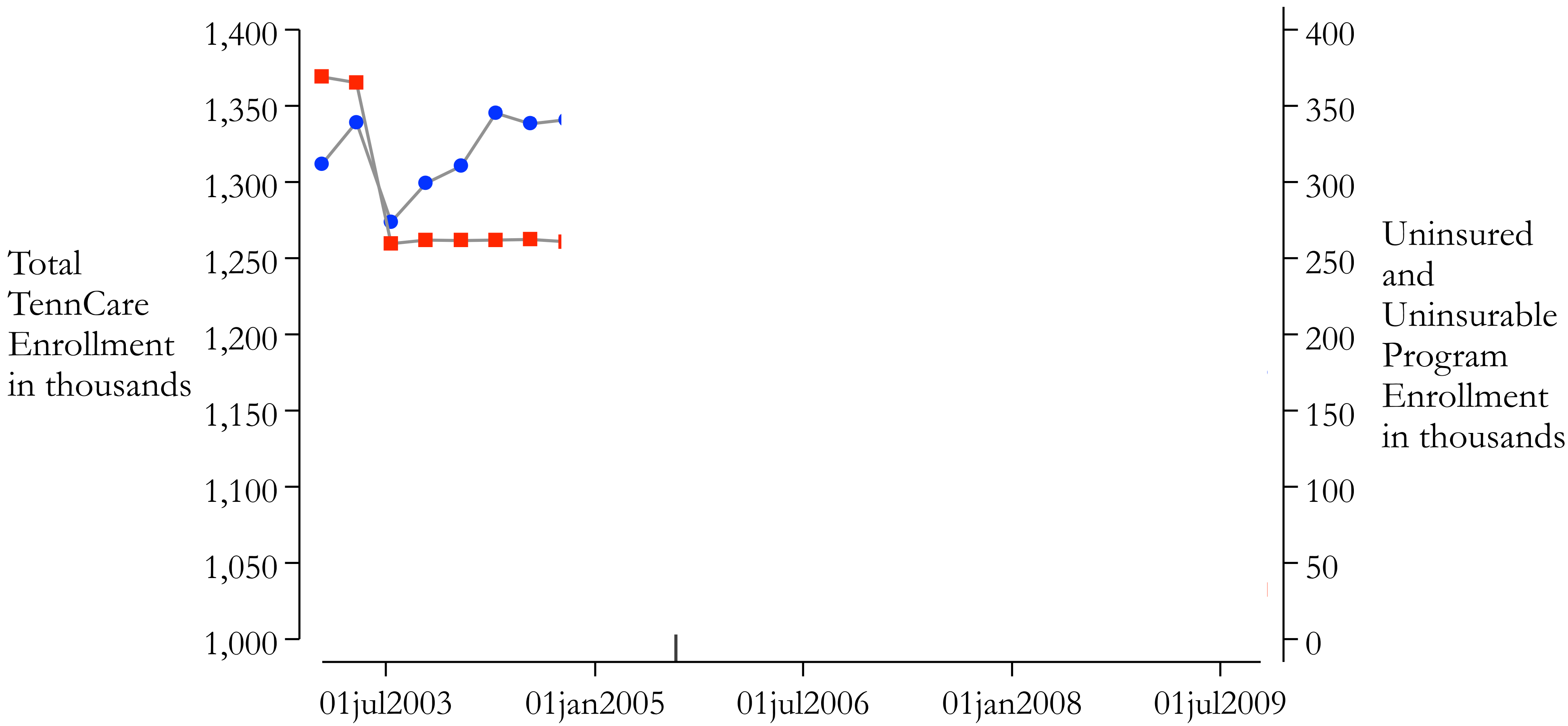
TennCare Population by Category



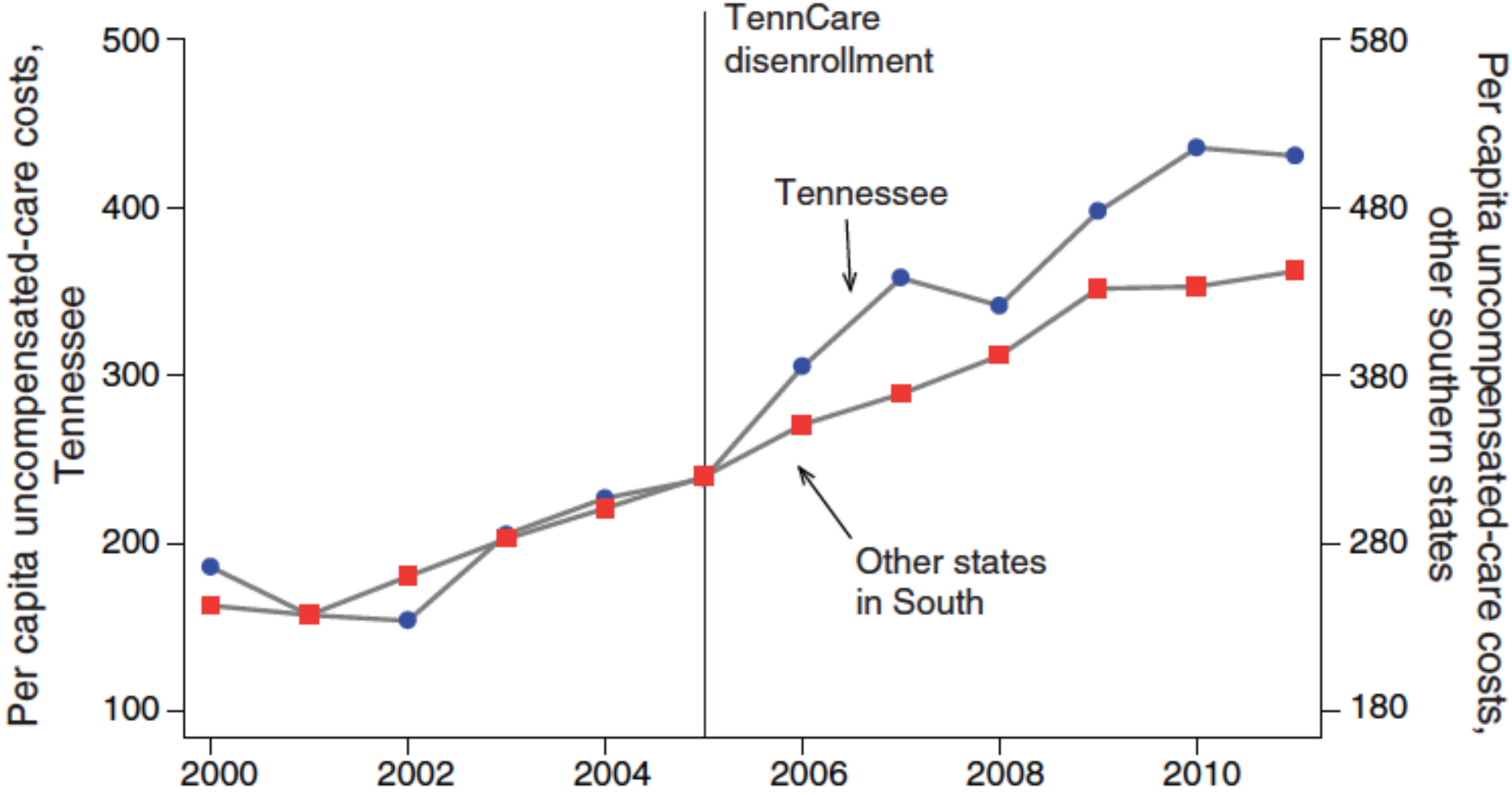


Figure 3. Uncompensated-Care Costs in Tennessee

Gartwaite et al. AEJ-Applied: Spillovers from hospital closures

Table 3—The Effect of a Hospital Closure on Uncompensated Care at Neighboring Hospitals

Dependent variable: The logarithm of uncompensated care or patient revenue				
Sample	Remaining hospitals	Total for commuting zone	Remaining nonprofit hospitals	Remaining for-profit hospitals
	(1)	(2)	(3)	(4)
Panel A. Uncompensated care				
Post closure	0.149	–0.061	0.173	0.004
	(0.052)	(0.054)	(0.068)	(0.203)
	[0.004]	[0.252]	[0.011]	[0.983]
R^2	0.959	0.959	0.940	0.863
Observations	12,952	12,953	10,139	3,250

Requirements of non-profits

1. Activities should be directed towards (tax-exempt) purpose that serve a public interest, not a private interest

2. **Lobbying activities allowed but cannot be "substantial" ("expenditure test")**

3. Prohibited from directly or indirectly participating in any political campaign

4. Cannot generate too much income from activities unrelated to the exempt function of non-profit organization

5. Annual reporting obligation and must operate "in accord with stated (tax-exempt) purpose"

Lobbying "expenditure test"

If the amount of exempt purpose expenditures is:	Lobbying nontaxable amount is:
≤ $500,000	20% of the exempt purpose expenditures
>$500,00 but ≤ $1,000,000	$100,000 plus 15% of the excess of exempt purpose expenditures over $500,000
> $1,000,000 but ≤ $1,500,000	$175,000 plus 10% of the excess of exempt purpose expenditures over $1,000,000
>$1,500,000 but ≤ $17,000,000	$225,000 plus 5% of the exempt purpose expenditures over $1,500,000
>$17,000,000	$1,000,000

Organizations electing to use the expenditure test must file Form 5768 PDF, *Election/Revocation of Election by an Eligible IRC Section 501(c)(3) Organization to Make Expenditures to Influence Legislation*, at any time during the tax year for which it is to be effective. The election remains in effect for succeeding years unless it is revoked by the organization. Revocation of the election is effective beginning with the year following the year in which the revocation is filed.

Under the expenditure test, an organization that engages in excessive lobbying activity over a four-year period may lose its tax-exempt status, making all of its income for that period subject to tax. Should the organization exceed its lobbying expenditure dollar limit in a particular year, it must pay an excise tax equal to 25 percent of the excess.

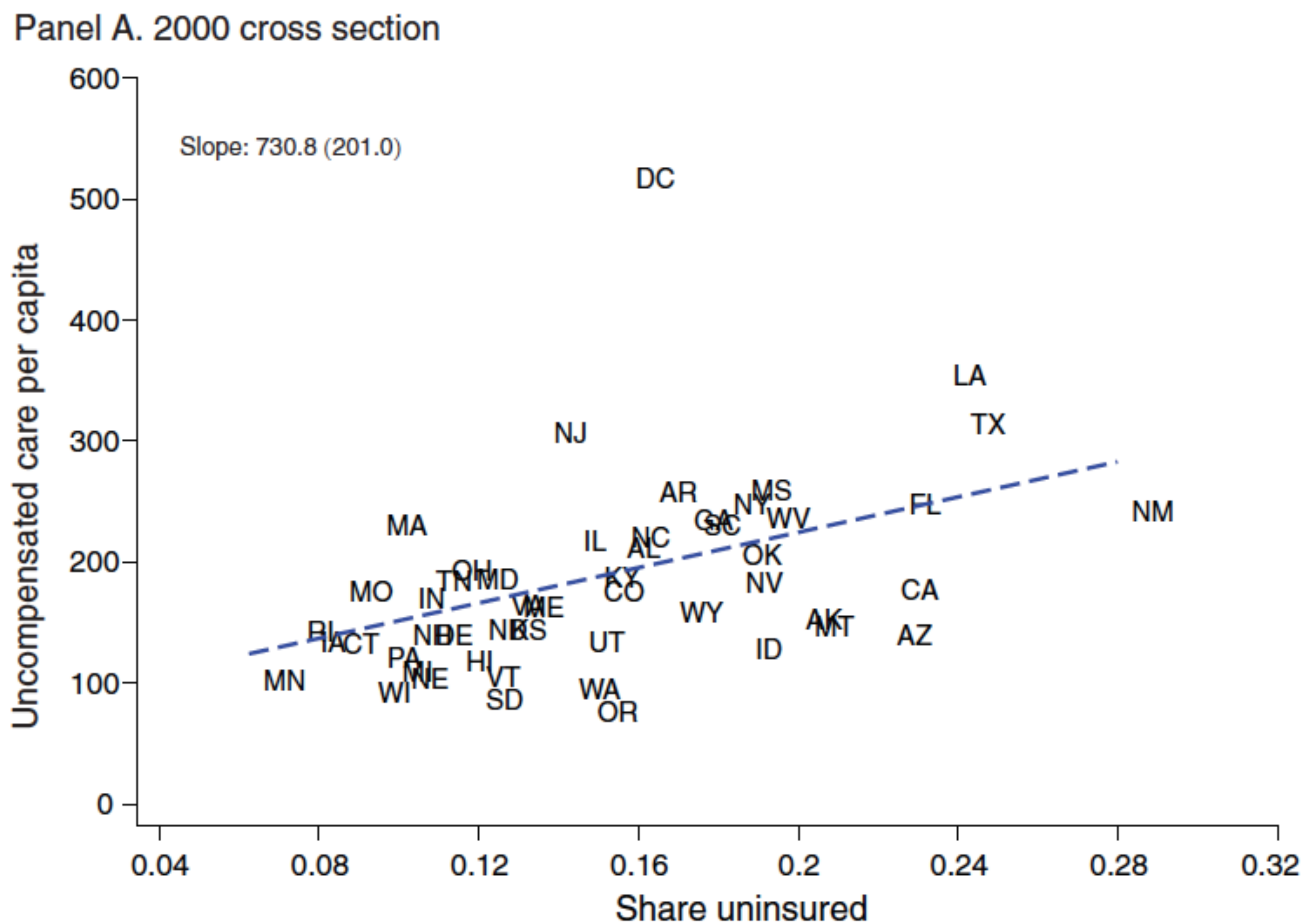
501(c)(3) versus 501(c)(6) non-profits

- Advocacy organizations can organize as 501(c)(6) organizations which are non-profit organizations that are allowed unlimited amounts of lobbying

- These organizations can advocate for common interests, but contributions are not considered charitable donations (and thus donations do not get same preferential tax treatment)

- For example, American Hospital Association, which is 501(c)(6) can advocate on behalf of non-profit hospitals, which are 501(c)(3) non-profits and thus face lobbying restrictions

Hospitals as "Insurers of Last Resort"



Hospitals as "Insurers of Last Resort"

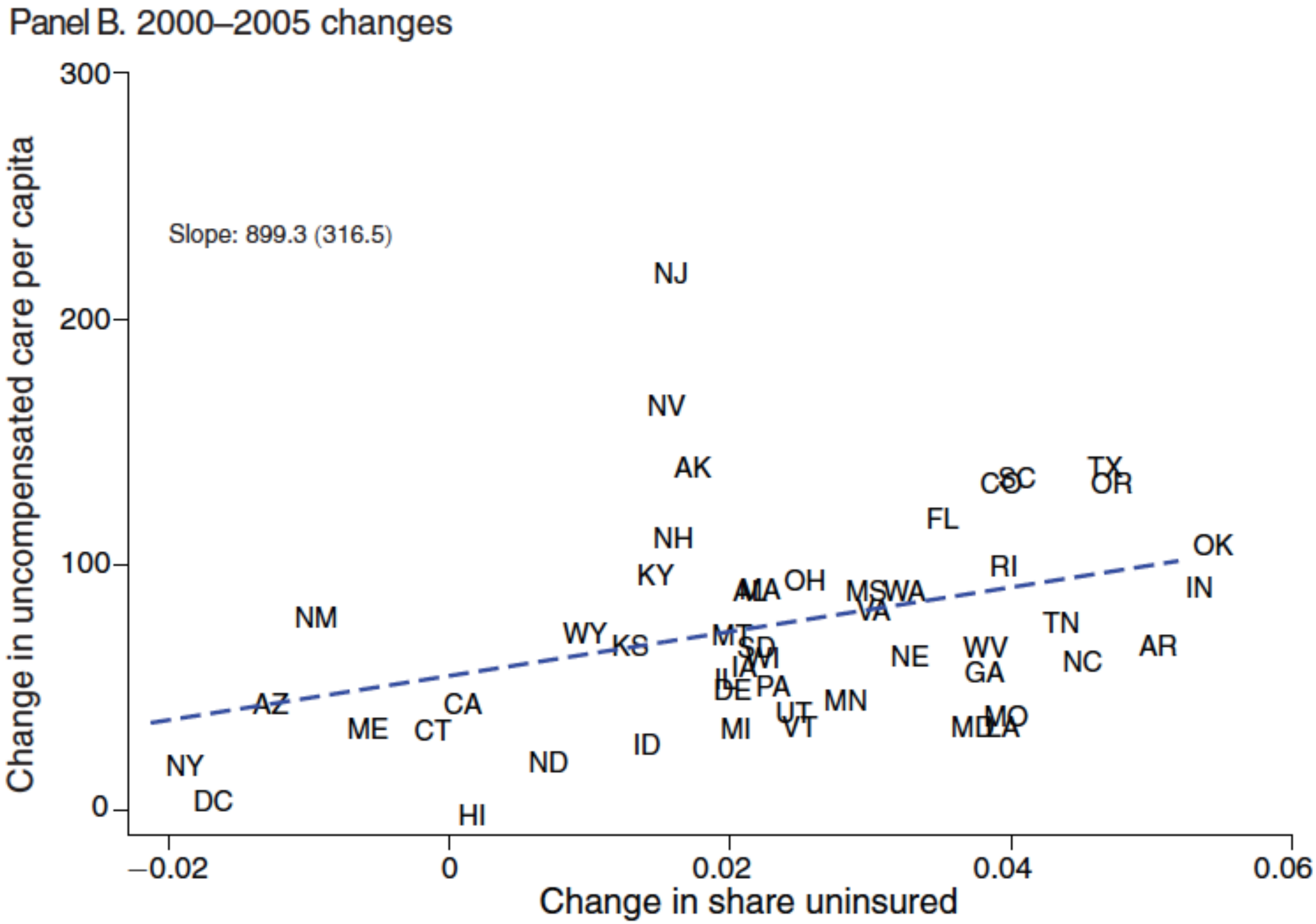


FIGURE 1. SHARE UNINSURED AND UNCOMPENSATED-CARE COSTS

Learning-by-Doing in Health Care
Overuse and Underuse in Healthcare
Machine Learning in Healthcare

AEA Continuing Education Program

CLASS #5

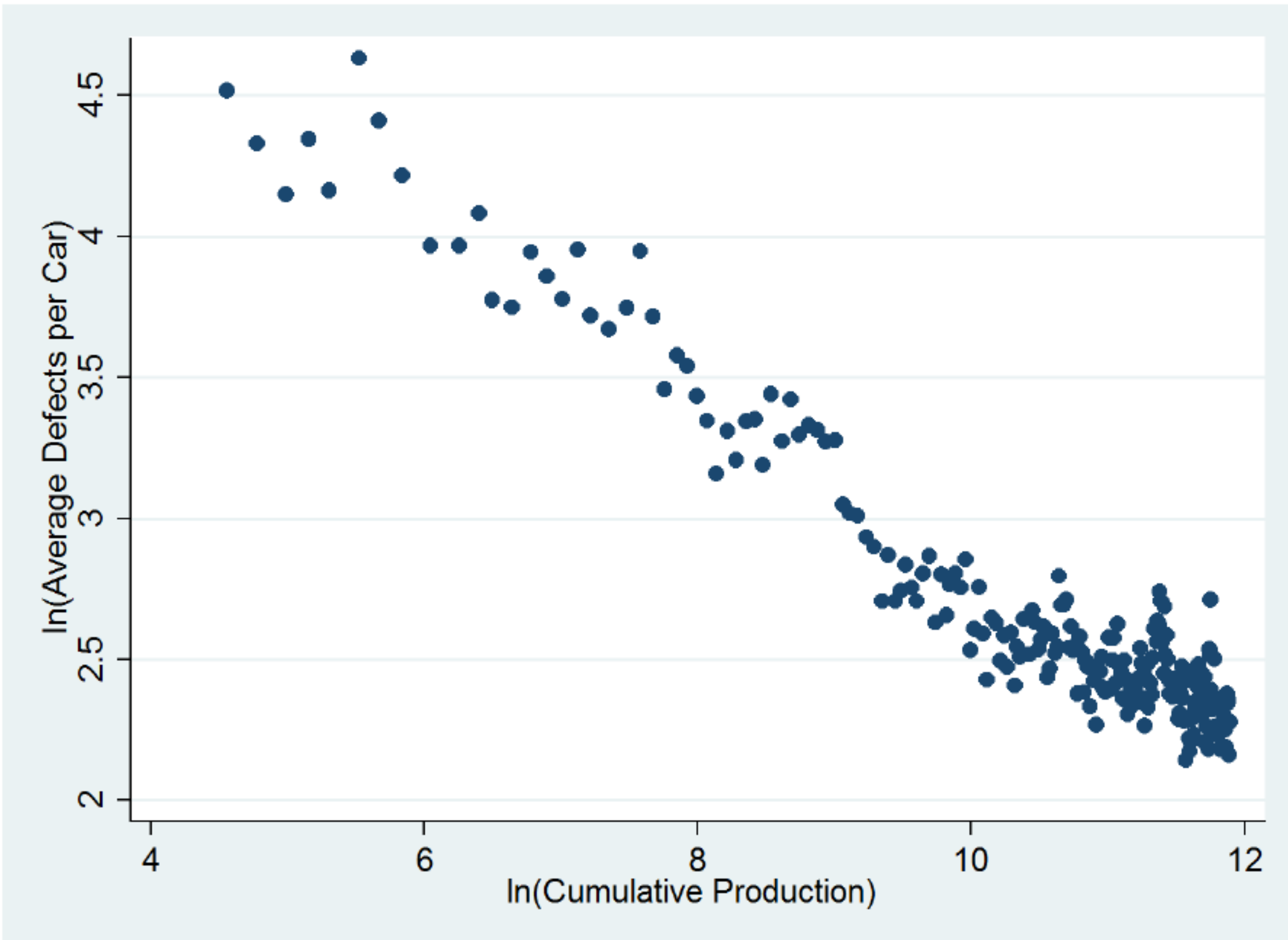
Matthew J. Notowidigdo ("Noto")
David McDaniel Keller Professor of Economics
University of Chicago Booth School of Business
Co-Director, Chicago Booth Healthcare Initiative
Co-Scientific Director, J-PAL North America
Research Associate, National Bureau of Economics Research

Outline

- Learning-by-Doing in Healthcare
- Overuse and Underuse in Healthcare
- Machine Learning in Healthcare

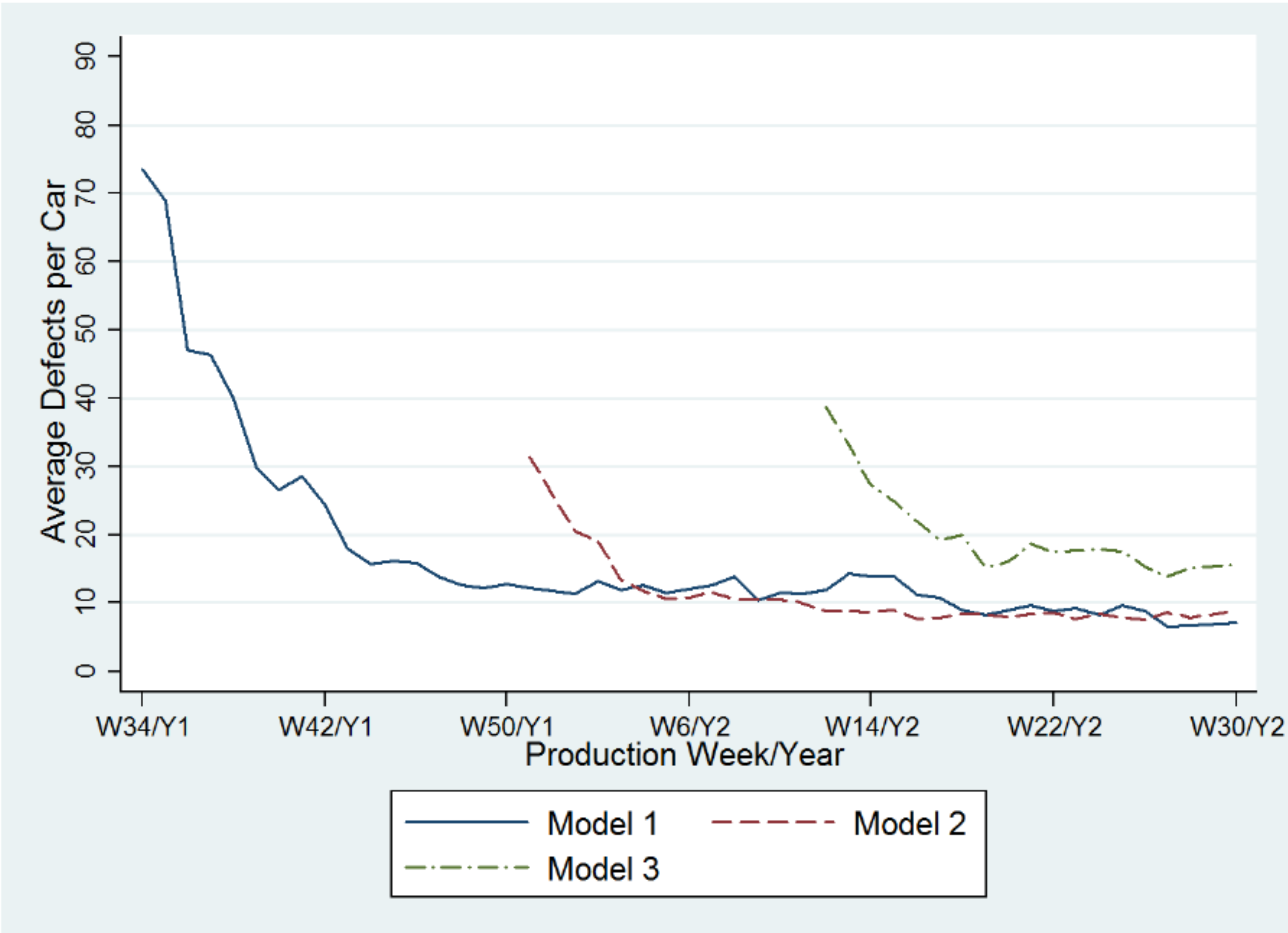
Learning-by-doing making cars (Levitt et al. JPE)

Figure 2. Log Defects per Car vs. Log Production Experience (Cumulative Output), Daily Data



Learning-by-doing making cars (Levitt et al. JPE)

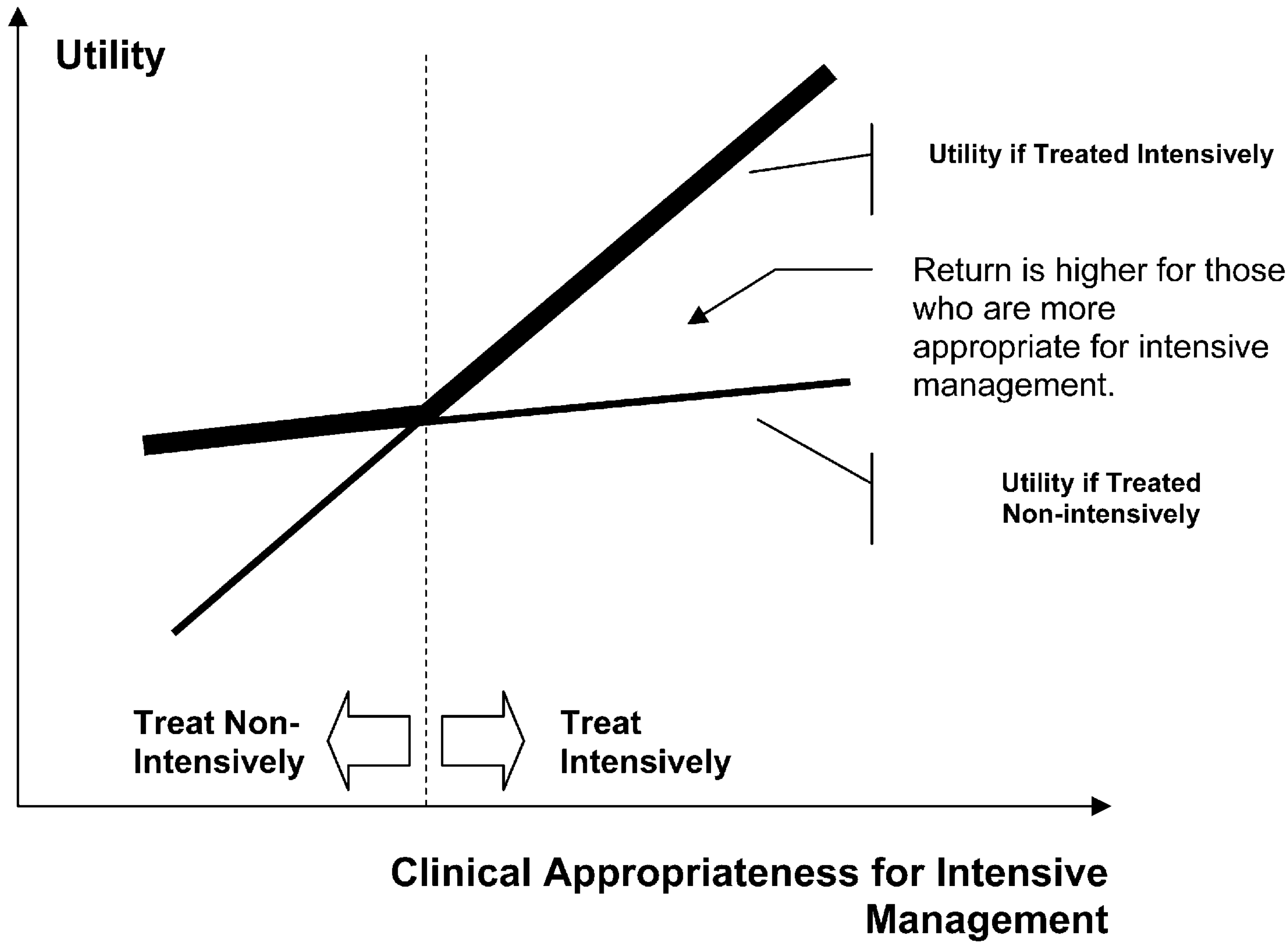
Figure 7. Average Defect Rates per Car, by Model Variant



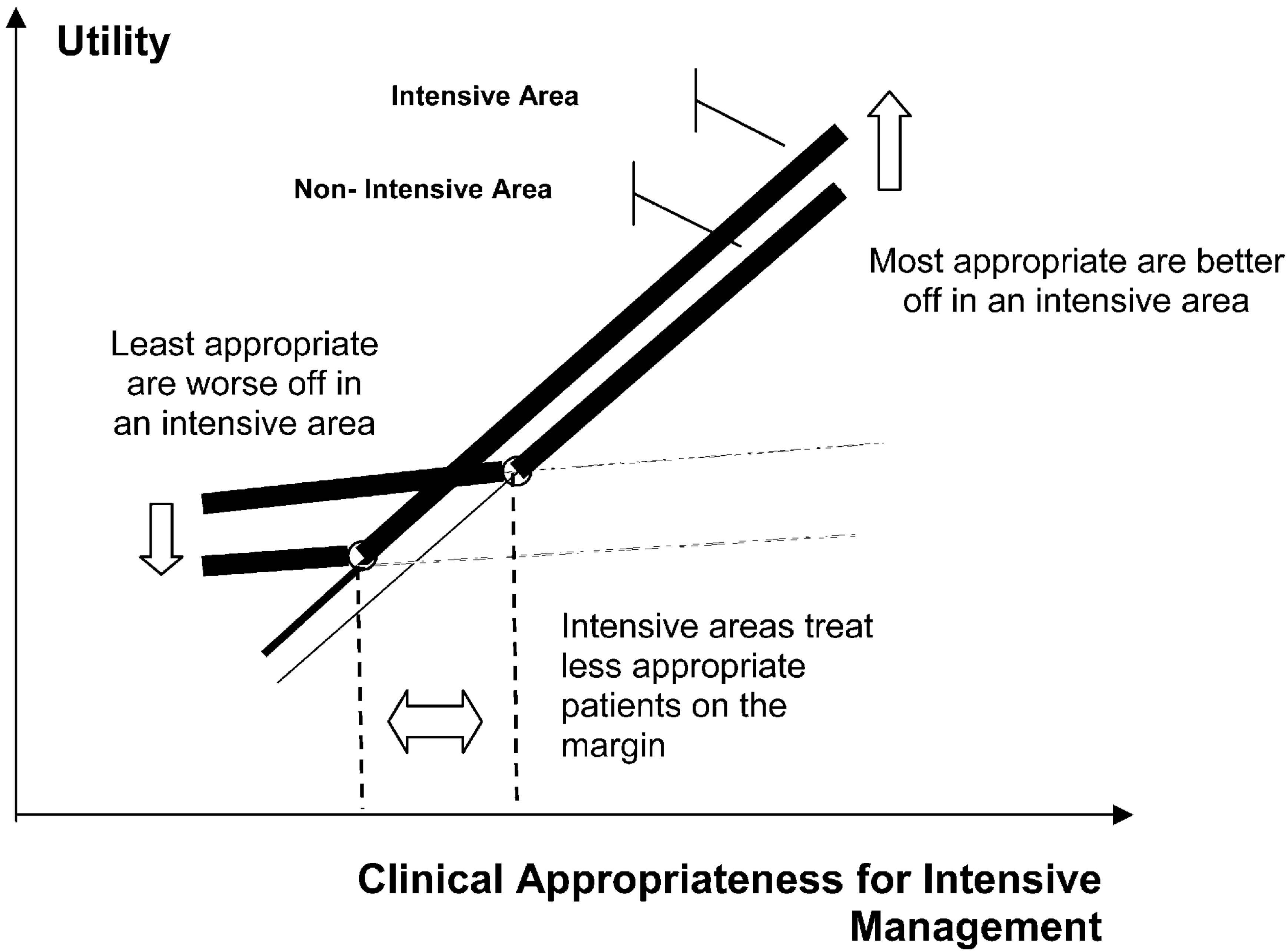
Treatment decisions after a heart attack

- Acute myocardial infarction (AMI) -- or "heart attack" -- is the primary manifestation of cardiovascular disease
- Cardiovascular disease is the leading cause of death in the US
- Post-AMI mortality is high (one-year survival rate in Medicare data is ~70 percent)
- AMI is an acute condition requiring immediate treatment
- Doctors must choose between "intensive" and "nonintensive" treatments in order to restore blood flow to the coronary arteries:
  1. [intensive] cardiac catheterization, angioplasty, bypass surgery
  2. [nonintensive] medical therapies such as thrombolysis

AMI treatment decision [Chandra-Staiger *JPE* Roy model]



Learning-by-doing and specialization



Variables that predict AMI treatment

TABLE A1
RISK ADJUSTERS INCLUDED IN THE MODEL

Age, race, sex (full interactions)	*hx* angina missing (ref = no)	Peak CK >1,000
Previous revascularization (1 = *y*)	*hx* terminal illness (1 = *y*)	Nonambulatory (ref = independent)
hx old MI (1 = *y*)	Current smoker	Ambulatory with assistance
hx CHF (1 = *y*)	Atrial fibrillation on admission	Ambulatory status missing
History of dementia	CPR on presentation	Albumin low (ref ≥3.0)
hx diabetes (1 = *y*)	Indicator MI = anterior	Albumin missing (ref ≥3.0)
hx hypertension (1 = *y*)	Indicator MI = inferior	Bilirubin high (ref <1.2)
hx leukemia (1 = *y*)	Indicator MI = other	Bilirubin missing (ref <1.2)
hx EF ≤40 (1 = *y*)	Heart block on admission	Creat 1.5–<2.0 (ref = <1.5)
hx metastatic cancer (1 = *y*)	CHF on presentation	Creat ≥2.0 (ref = <1.5)
hx nonmetastatic cancer (1 = *y*)	Hypotensive on admission	Creat missing (ref = <1.5)
hx PVD (1 = *y*)	Hypotensive missing	Hematocrit low (ref = >30)
hx COPD (1 = *y*)	Shock on presentation	Hematocrit missing (ref = >30)
hx angina (ref = no)	Peak CK missing	Ideal for cath (ACC/AHA criteria)

Effect of catheterization on survival

TABLE 1
INSTRUMENTAL VARIABLE ESTIMATES OF INTENSIVE MANAGEMENT AND SPENDING ON ONE-YEAR SURVIVAL BY CLINICAL APPROPRIATENESS OF PATIENT

	INSTRUMENTAL VARIABLE ESTIMATES OF		
	Impact of Cath		
SAMPLE	On One-Year Survival (1)	On One-Year Cost ($1,000s) (2)	Impact of $1,000 on One-Year Survival (3)
A. All patients (N = 129,895)	.142	9.086	.016
	(.036)	(1.810)	(.005)
B. By cath propensity:			
Above the median (N = 64,799)	.184	4.793	.038
	(.034)	(1.997)	(.017)
Below the median (N = 65,096)	.035	17.183	.002
	(.083)	(3.204)	(.005)
Difference	.149	−12.39	.036
	(.090)	(3.775)	(.018)
C. By age:			
65–80 (N = 89,947)	.171	6.993	.024
	(.037)	(1.993)	(.009)
Over 80 (N = 39,948)	.016	16.026	.001
	(.108)	(2.967)	(.007)
Difference	.155	−9.033	.023
	(.114)	(3.574)	(.011)

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Above the median (N = 64,799)	.184	4.793	.038
	(.034)	(1.997)	(.017)
Below the median (N = 65,096)	.035	17.183	.002
	(.083)	(3.204)	(.005)
Difference	.149	−12.39	.036
	(.090)	(3.775)	(.018)
C. By age:			
65–80 (N = 89,947)	.171	6.993	.024
	(.037)	(1.993)	(.009)
Over 80 (N = 39,948)	.016	16.026	.001
	(.108)	(2.967)	(.007)
Difference	.155	−9.033	.023
	(.114)	(3.574)	(.011)

Effect of catheterization by HRR

TABLE 6
INSTRUMENTAL VARIABLE ESTIMATES OF INTENSIVE MANAGEMENT AND SPENDING ON SURVIVAL, BY SURGICAL INTENSITY OF HOSPITAL REFERRAL REGION

	Instrumental Variable Estimates of		
	Impact of Cath		
Sample	On One-Year Survival (1)	On One-Year Cost ($1,000s) (2)	Impact of $1,000 on One-Year Survival (3)
A. All patients:			
HRR risk-adjusted cath rate:			
Above the median (N = 63,771)	.256	6.691	.038
	(.061)	(3.510)	(.021)
Below the median (N = 66,124)	.09	9.835	.009
	(.059)	(3.155)	(.007)
Difference	.166	−3.144	.029
	(.085)	(4.720)	(.022)
B. Patients above the median cath propensity:			
HRR risk-adjusted cath rate:			
Above the median (N = 32,388)	.271	.347	.78
	(.064)	(4.370)	(9.820)
Below the median (N = 32,411)	.168	4.962	.034
	(.046)	(2.890)	(.021)
C. Patients below the median cath propensity:			
HRR risk-adjusted cath rate:			
Above the median (N = 31,383)	.206	16.21	.013
	(.129)	(5.130)	(.009)
Below the median (N = 33,713)	−.139	22.064	−.006
	(.165)	(6.870)	(.007)

Identifying Inefficiency (Overuse and Underuse)

- Chandra-Staiger QJE 2020 extend Roy model from earlier work to distinguish overuse and underuse from differences in expertise

Actual (realized) survival if receiving usual care or reperfusion is equal to expected survival plus a random error term $(\varepsilon_{ih}^{0}, \varepsilon_{ih}^{1})$, which yields survival equations of the following form:

$$\text{(1a)} \qquad Y_{ih}^{0} = E(Y_{ih}^{0}) + \varepsilon_{ih}^{0} = \boxed{\alpha_h^{0}} + X_i\beta_h^{0} + v_{ih}^{0} + \varepsilon_{ih}^{0},$$

$$\text{(1b)} \qquad Y_{ih}^{1} = E(Y_{ih}^{1}) + \varepsilon_{ih}^{1} = \boxed{\alpha_h^{1}} + X_i\beta_h^{1} + v_{ih}^{1} + \varepsilon_{ih}^{1}.$$

The benefit, or gain, or return, from reperfusion treatment for patient i in hospital h is Y_{ih}^{Δ} given by:

$$\text{(1c)} \qquad Y_{ih}^{\Delta} = \alpha_h^{\Delta} + X_i\beta_h^{\Delta} + v_{ih}^{\Delta} + \varepsilon_{ih}^{\Delta},$$

where $\alpha_h^{\Delta} = \alpha_h^{1} - \alpha_h^{0}$, $\beta_h^{\Delta} = \beta_h^{1} - \beta_h^{0}$, $v_{ih}^{\Delta} = v_{ih}^{1} - v_{ih}^{0}$, and $\varepsilon_{ih}^{\Delta} = \varepsilon_{ih}^{1} - \varepsilon_{ih}^{0}$.

Similarly, the expected benefit from reperfusion at the time of choosing treatment is given by:

$$\text{(1d)} \qquad E\left(Y_{ih}^{\Delta}\right) = \alpha_h^{\Delta} + X_i\beta_h^{\Delta} + v_{ih}^{\Delta}.$$

Identifying Inefficiency (Overuse and Underuse)

- Chandra-Staiger QJE 2020 extend Roy model from earlier work to distinguish overuse and underuse from differences in expertise

Actual (realized) survival if receiving usual care or reperfusion is equal to expected survival plus a random error term $(\varepsilon^0_{ih}, \varepsilon^1_{ih})$, which yields survival equations of the following form:

(1a) $$Y^0_{ih} = E(Y^0_{ih}) + \varepsilon^0_{ih} = \alpha^0_h + X_i\beta^0_h + v^0_{ih} + \varepsilon^0_{ih},$$

(1b) $$Y^1_{ih} = E(Y^1_{ih}) + \varepsilon^1_{ih} = \alpha^1_h + X_i\beta^1_h + v^1_{ih} + \varepsilon^1_{ih}.$$

The benefit, or gain, or return, from reperfusion treatment for patient i in hospital h is Y^Δ_{ih} given by:

(1c) $$Y^\Delta_{ih} = \alpha^\Delta_h + X_i\beta^\Delta_h + v^\Delta_{ih} + \varepsilon^\Delta_{ih},$$

where $\alpha^\Delta_h = \alpha^1_h - \alpha^0_h$, $\beta^\Delta_h = \beta^1_h - \beta^0_h$, $v^\Delta_{ih} = v^1_{ih} - v^0_{ih}$, and $\varepsilon^\Delta_{ih} = \varepsilon^1_{ih} - \varepsilon^0_{ih}$.

Similarly, the expected benefit from reperfusion at the time of choosing treatment is given by:

(1d) $$\boxed{E\left(Y^\Delta_{ih}\right) = \alpha^\Delta_h + X_i\beta^\Delta_h + v^\Delta_{ih}.}$$

Identifying Inefficiency (Overuse and Underuse)

- Chandra-Staiger QJE 2020 extend Roy model from earlier work

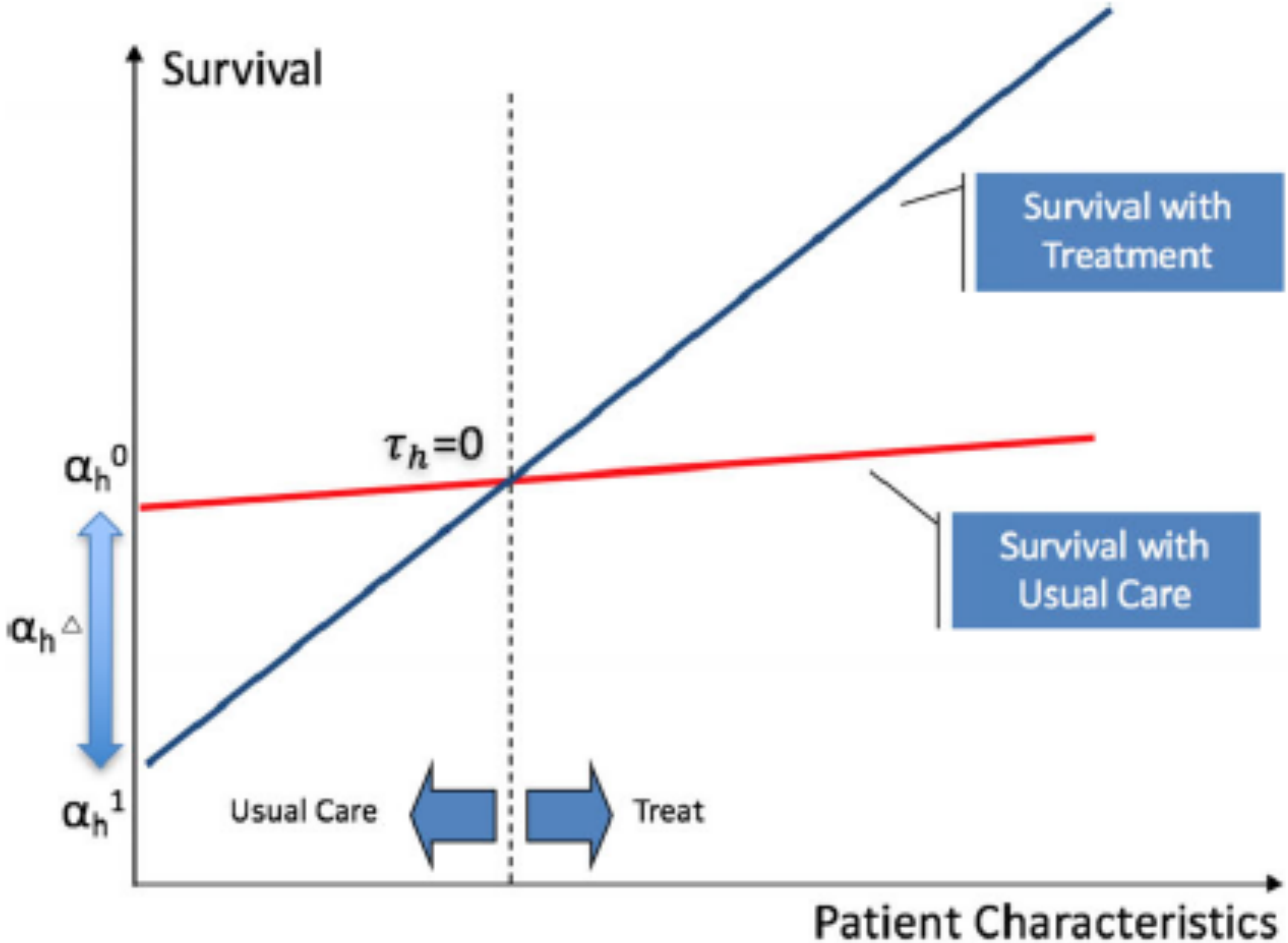
III.B. Treatment Choice

A patient receives treatment if the expected benefit from treatment exceeds a minimal threshold τ_h, where the threshold may vary across hospitals due to incentives or information, as discussed further below. Since $E(Y_{ih}^{\Delta})$ captures the total expected benefit to the patient of providing treatment, the optimal decision from the patient's perspective would let $\tau_h = 0$ and provide treatment whenever the expected benefits to the patient exceed 0. There is underuse if $\tau_h > 0$, because patients with positive benefits are under the threshold and do not receive treatment. There is overuse if $\tau_h < 0$, since patients with negative benefits (who would do better without treatment) are above the threshold and receive treatment.

of choosing treatment is given by:

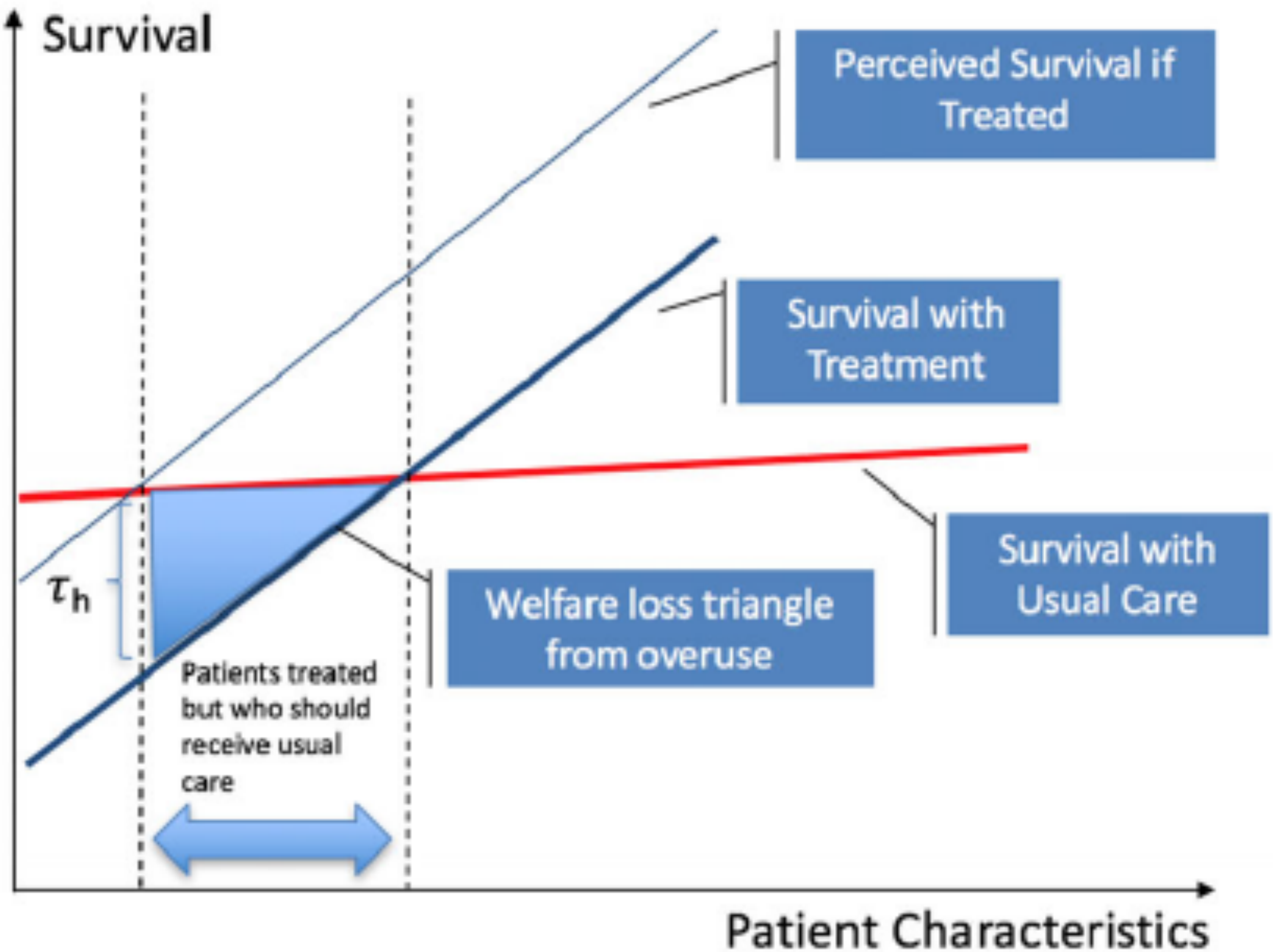
$$E\left(Y_{ih}^{\Delta}\right) = \alpha_h^{\Delta} + X_i\beta_h^{\Delta} + v_{ih}^{\Delta}. \tag{1d}$$

Identifying Inefficiency (Overuse and Underuse)



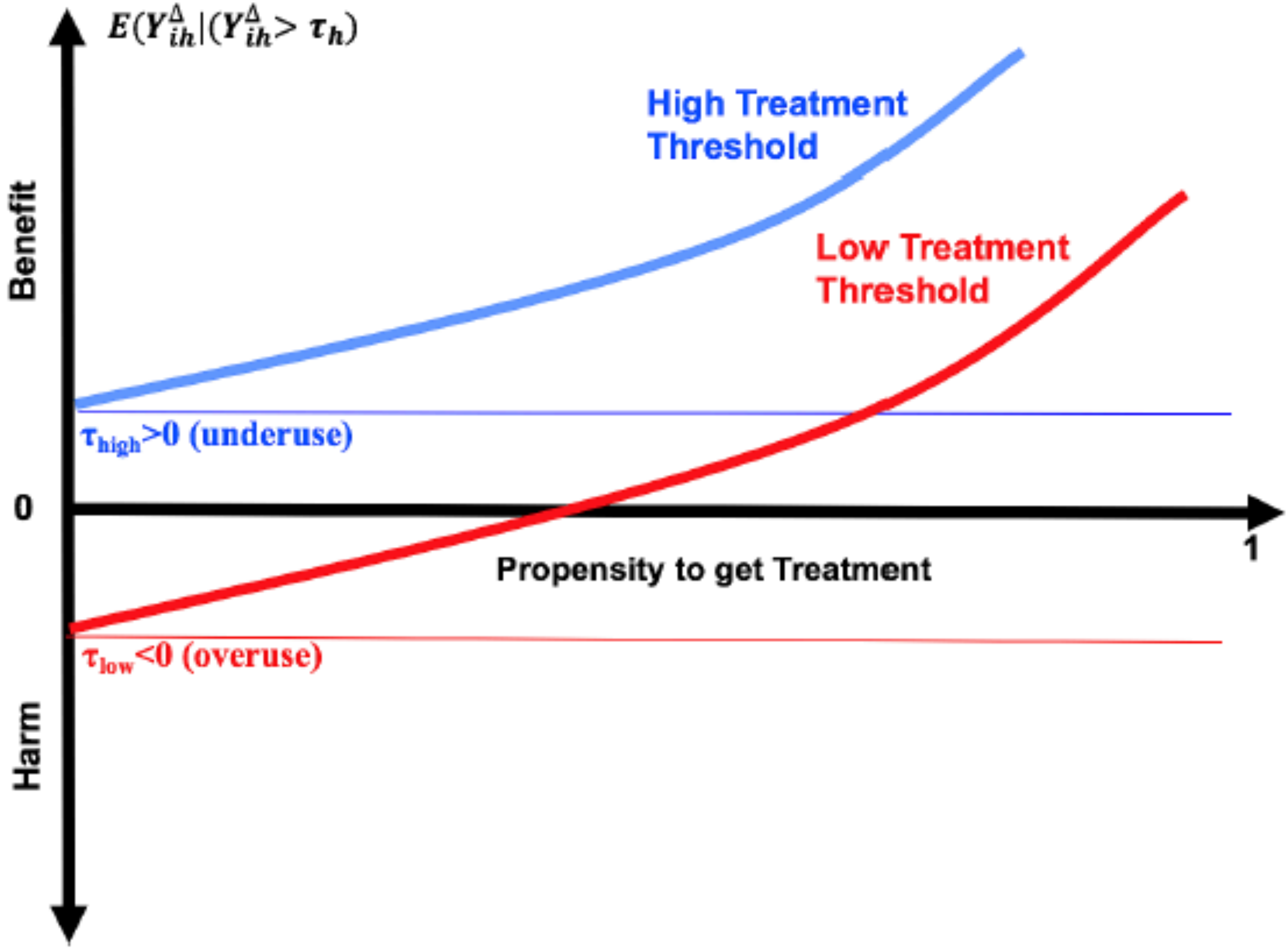
(A) A Roy Model of Treatment at the Hospital Level

Identifying Inefficiency (Overuse and Underuse)



(B) A Roy Model of Treatment at the Hospital Level with Allocative Inefficiency

Identifying Inefficiency (Overuse and Underuse)



Identifying Inefficiency (Overuse and Underuse)

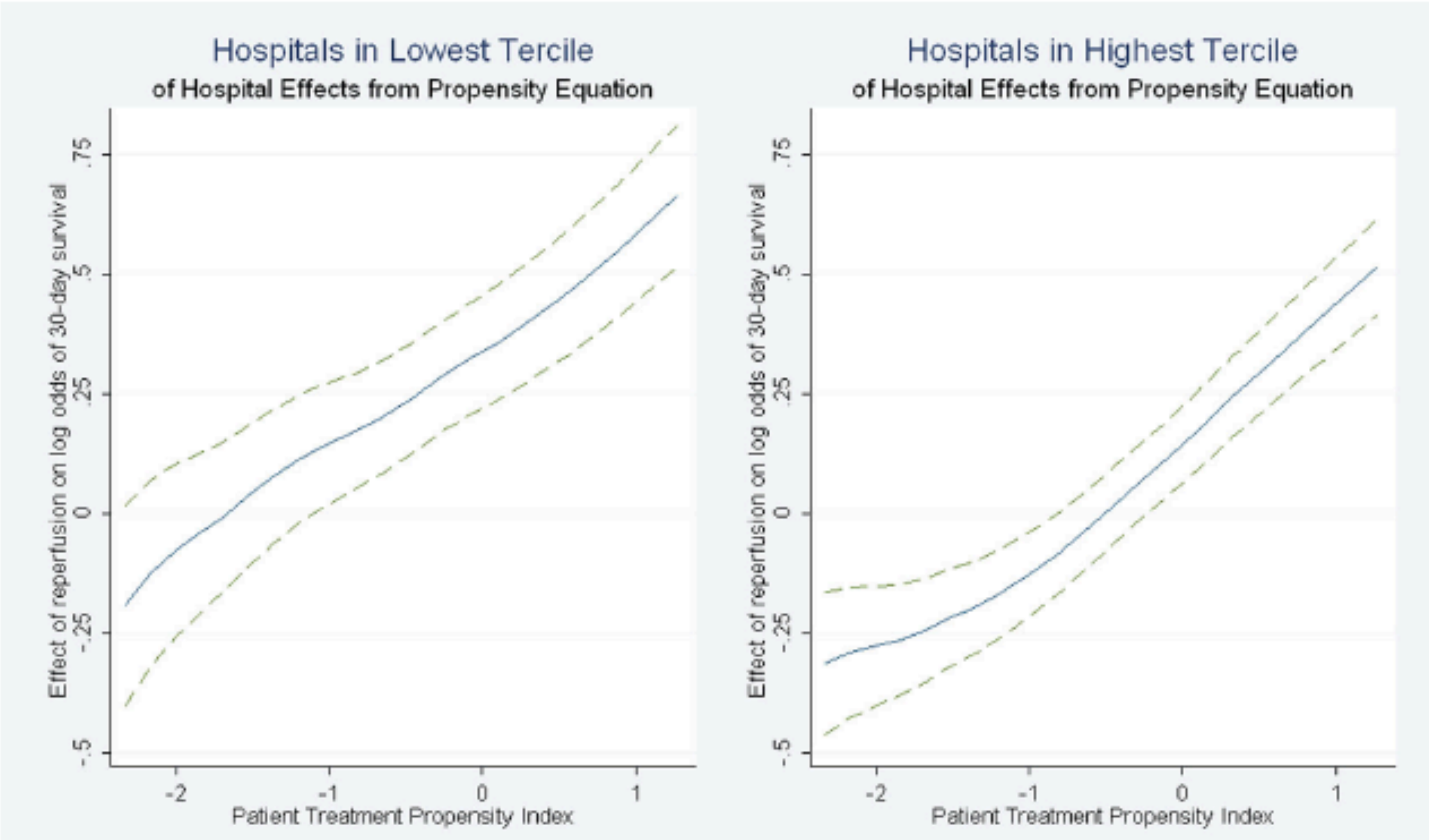


FIGURE IV

Survival Benefit from Reperfusion by Patient's Treatment Propensity, Low Treatment Rate (Left) and High Treatment Rate (Right) Hospitals

Identifying Inefficiency (Overuse and Underuse)

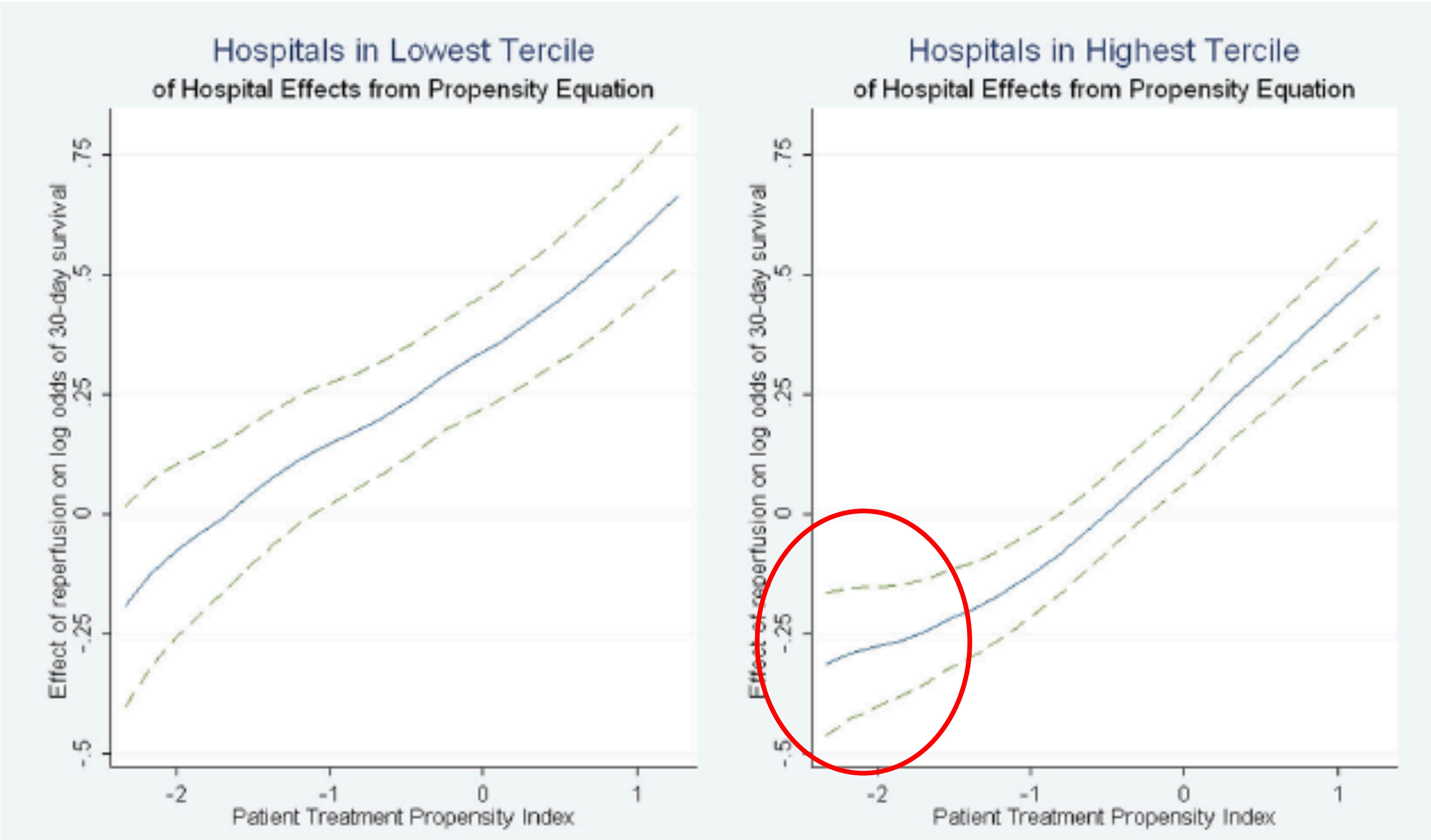


FIGURE IV

Survival Benefit from Reperfusion by Patient's Treatment Propensity, Low Treatment Rate (Left) and High Treatment Rate (Right) Hospitals

Identifying Inefficiency (Overuse and Underuse)

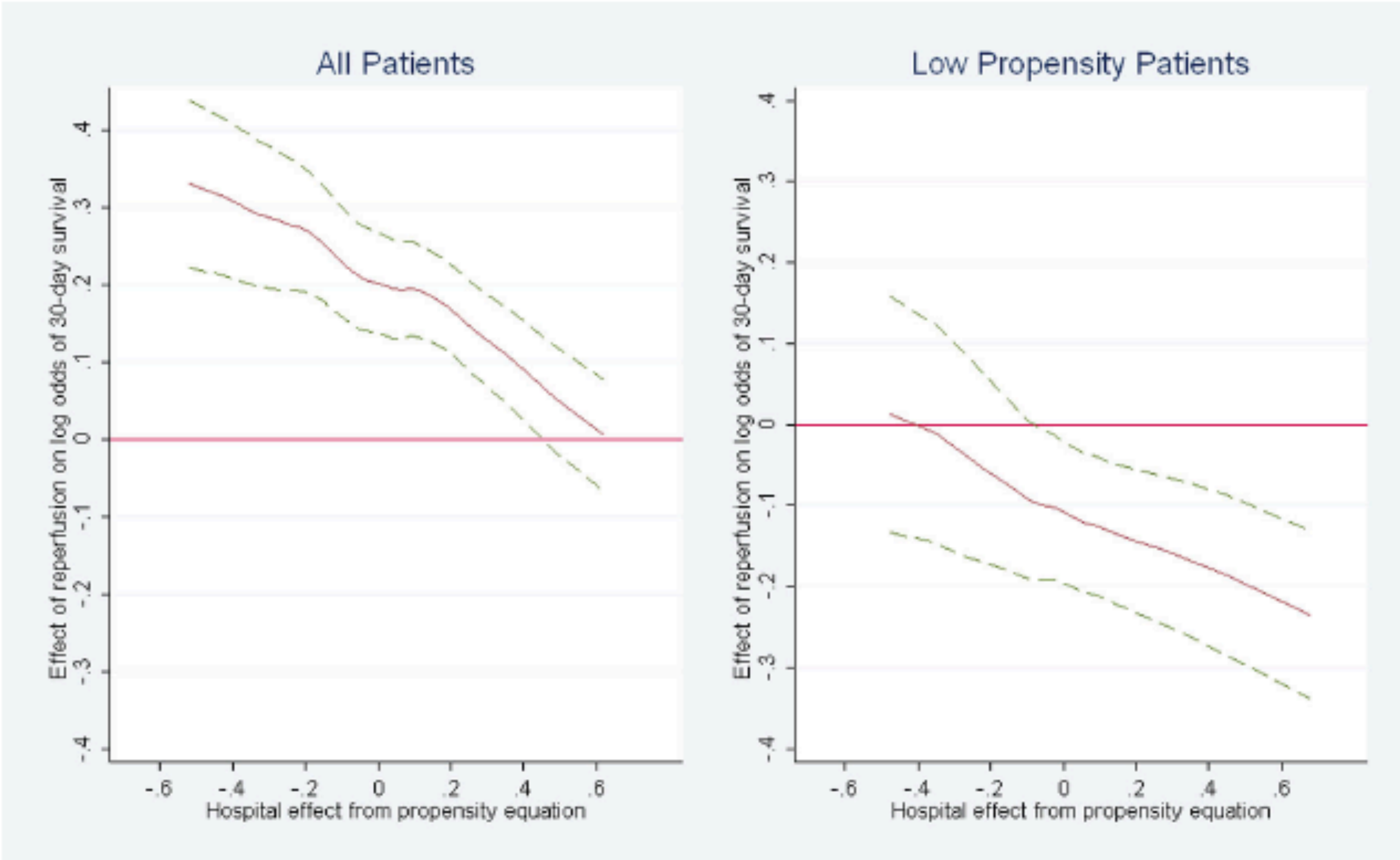


FIGURE V

Survival Benefit from Reperfusion by Risk-Adjusted Hospital Treatment Rate, All Patients (Left) and Low-Propensity Patients (Right)

Identifying Inefficiency (Overuse and Underuse)

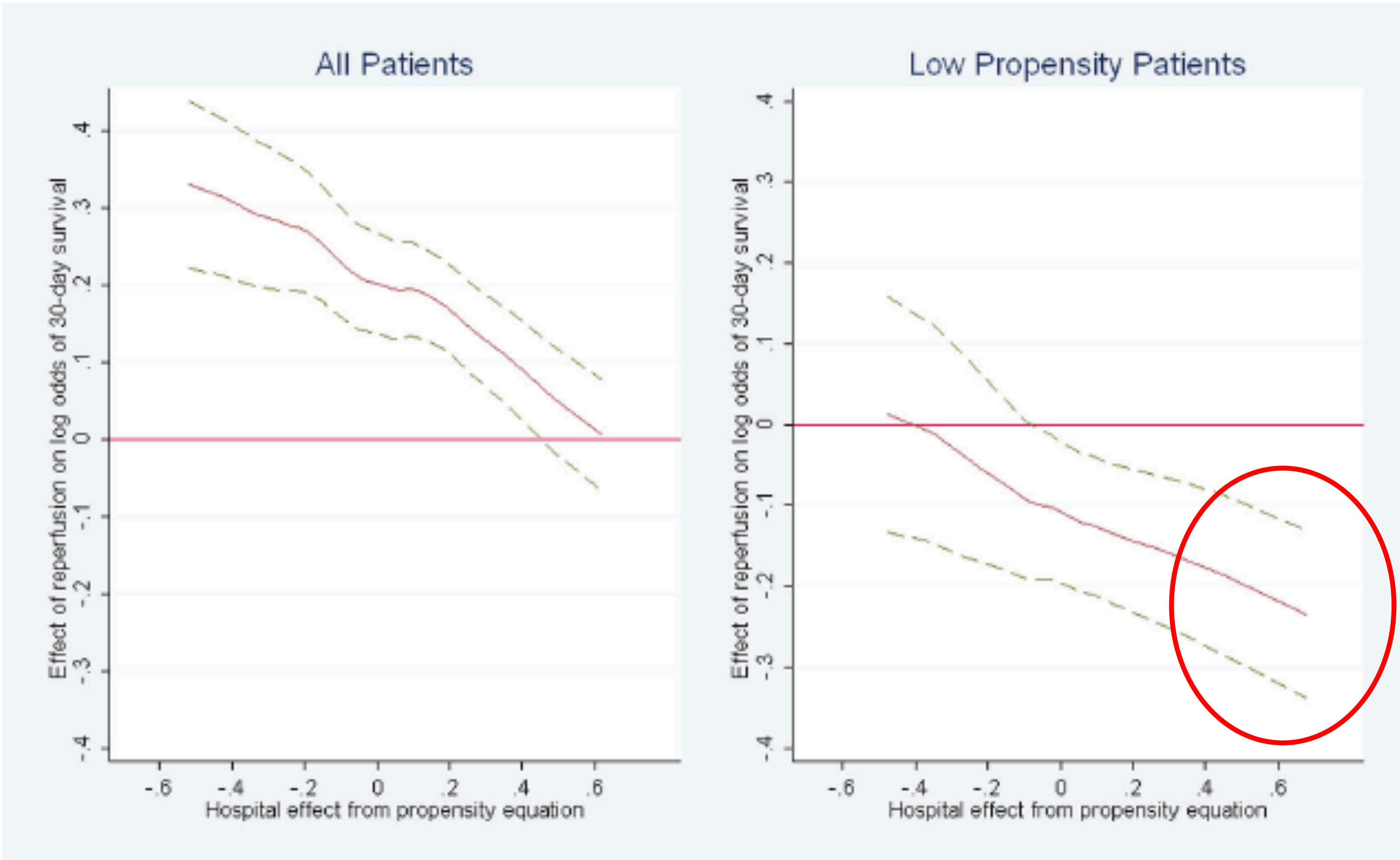


FIGURE V

Survival Benefit from Reperfusion by Risk-Adjusted Hospital Treatment Rate, All Patients (Left) and Low-Propensity Patients (Right)

Identifying Inefficiency (Overuse and Underuse)

TABLE III

EFFECT OF REPERFUSION ON 7-DAY AND 360-DAY SURVIVAL, LOGIT ESTIMATES

	Conditional on propensity (1)	Conditional on propensity (2)
Panel A: 7-day survival		
Reperfusion	0.218	Nonparametric
	(0.031)	
Reperfusion $*$ propensity index	0.356	Nonparametric
	(0.021)	
Reperfusion $*$ hospital treatment rate (θ)	−0.271	−0.325
	(0.087)	(0.088)
Control for propensity index	Linear	Nonparametric
Panel B: 360-day survival		
Reperfusion	0.393	Nonparametric
	(0.023)	
Reperfusion $*$ propensity index	0.176	Nonparametric
	(0.017)	
Reperfusion $*$ hospital treatment rate (θ)	−0.147	−0.192
	(0.066)	(0.067)
Control for propensity index	Linear	Nonparametric

Identifying Inefficiency (Overuse and Underuse)

TABLE IV

EFFECT OF REPERFUSION ON 30-DAY SURVIVAL, MIXED-LOGIT ESTIMATES

	(1)	(2)
Reperfusion	0.297	0.314
	(0.022)	(0.024)
Reperfusion $*$ propensity index	0.289	0.292
	(0.017)	(0.017)
Std. dev. of hospital intercept (α^0)	0.188	0.198
	(0.015)	(0.017)
Hospital-level random intercept (α^0)	Yes	Yes
Hospital-level random coefficient on reperfusion (τ)	No	Yes
Std. dev. of hospital coefficient on reperfusion		0.313
(identifies τ; hospital-level thresholds)		(0.056)
corr(hospital-level intercept, coefficient on reperfusion)		−0.331
(identifies corr (α^0, τ))		(0.154)
Number of hospitals	4,690	4,690

Notes. Coefficients are log odds. Propensity equation is Pr(reperfusion) = F($X\beta$ + hospital effect) and is estimated using a logit model; see Online Appendix II. Propensity index refers to the logit index ($X\beta$ + hospital effect). It is demeaned to the average value of patients receiving reperfusion. The table reports estimates of equation (6a). All models include all CCP risk adjusters. The sample size in every regression is 138,957.

Cardiac catherization as a diagnostic test

- The previous slides have focused on the “intensive versus nonintensive” treatment decision following a heart attack
- We can also think about the doctors as having access to tests to determine the appropriate treatment decision
- Example: Patient arrives in the ER complaining of chest pain; ER doctors can do tests to determine whether there is a new blockage
- Before any intensive treatment is done, some combination of several tests are typically carried out: ECG, troponin (lab test), stress testing, and cardiac catheterization

Question: Are doctors over-testing a lot, under-testing a lot, neither, or both? (Another kind of overuse/underuse)

When to do (costly and imperfect) tests

- Testing can provide information about the most appropriate treatment decision
- The value of a test is directly related to the value of the information it can provide
- If you already know the outcome of the test, then the test is not providing information (maybe it’s “confirming” what you already know, but it’s not going to change the treatment)
- Many tests in medicine are imperfect, with both false positives and false negatives

Classifying results from imperfect tests

Suppose there is a test T, and the test has a false positive rate of p and a true positive rate of q. This implies that the false negative rate is 1-q and the true negative rate is 1-p

		COVID status	
		Has COVID	Does not have COVID
Test result	Positive	TP	FP
	Negative	FN	TN

Sensitivity: q = TP / (TP + FN)

Specificity: 1-p = TN / (FP + TN)

Positive predicted value: TP / (TP + FP)

= q * prevalence / (q * prevalence + p * (1 - prevalence))

Classifying results from imperfect tests

Suppose there is a test *T*, and the test has a false positive rate of *p* and a true positive rate of *q*. This implies that the false negative rate is 1-*q* and the true negative rate is 1-*p*

		COVID status	
		Has COVID	Does not have COVID
Test result	Positive	TP	FP
	Negative		

Sensitivity: q = TP / (TP + FN)

Specificity: 1-p = TN / (FP + TN)

Positive predicted value: TP / (T

= q * prevalence / (q * prevale

<u>Example:</u> COVID-19 rapid tests have fairly high specificity (88%-96%), but possibly very low sensitivity (36%-96%)

Surveillance testing

		COVID status	
		Has COVID	Does not have COVID
Test result	Positive	TP	FP
	Negative	FN	TN

2,000 students tested using rapid test, and 20 actually have COVID

Assume q = 0.65, 1-p = 0.90

How many test positive?

What is the positive predicted value?

How many true positives are “missed”?

Surveillance testing

		COVID status	
		Has COVID	Does not have COVID
Test result	Positive	TP	FP
	Negative	FN	TN

2,000 students tested using rapid test, and 20 actually have COVID

Assume *q* = 0.65, 1-*p* = 0.90

How many test positive? **13**

What is the positive predicted value? **13/(13+198) = 0.06**

How many true positives are "missed"? **7**

Surveillance testing

		COVID status	
		Has COVID	Does not have COVID
Test result	Positive	TP	FP
	Negative	FN	TN

2,000 students tested using rapid test, and 20 actually have COVID

Assume *q* = 0.65, 1-*p* = ~~0.90~~ 0.99

How many test positive?

What is the positive predicted value?

How many true positives are "missed"?

Surveillance testing

		COVID status	
		Has COVID	Does not have COVID
Test result	Positive	TP	FP
	Negative	FN	TN

2,000 students tested using rapid test, and 20 actually have COVID

Assume *q* = 0.65, 1-*p* = ~~0.90~~ 0.99

How many test positive? **13**

What is the positive predicted value? **13/(13+20) = 0.40**

How many true positives are “missed”? **7**

Coronary angiogram imaging tests (CTCA)

- Coronary angiogram imaging tests (CTCA) have very(!) high specificity and sensitivity (~99%)
- Thus, coronary angiograms are very valuable diagnostic tools (but they are more expensive than COVID-19 tests!)
- We will say a test has a **“high yield”** if the probability that it detects a blockage is high; otherwise it is **“low yield”**
- We will say doctors are **over-testing** if we can find groups where we can predict their negative test result with very high confidence
- We will say doctors are **under-testing** if we can find groups who are <u>not</u> tested and who later experience adverse health outcomes

Using machine learning to study over-testing and under-testing

- Mullainathan and Obermeyer *QJE* 2023 use a **machine learning** model that starts with 16,405 patient characteristics: patient demographics; all diagnoses, procedures, lab results, vital signs measured anytime over last 2 years prior to an ED visit; all symptoms recorded at ED triage desk at start of visit
- Authors conclude that the machine learning model can reliably predict negative tests a large share of the time (they claim they can get rid of 62% of tests at a $150,000 QALY threshold)
- They conclude that eliminating "stress testing" altogether would achieve large savings, as well

[Review] What's a QALY?

- QALY = Quality-adjusted life year
- Used in cost-benefit analysis
- 1 QALY = 1 year in perfect health
- Related to VSLY (Value of a statistical life-year), but accounts for both changes in length of life and quality of life
- In some high-income countries (UK, Netherlands), QALYs used to allocate healthcare resources and determine cost-effectiveness of new treatments
- Congress banned use of QALYs in Medicare around the same time the "death panel" misinformation campaign was being carried out during Obamacare policy debate

Source: https://en.wikipedia.org/wiki/Quality-adjusted_life_year

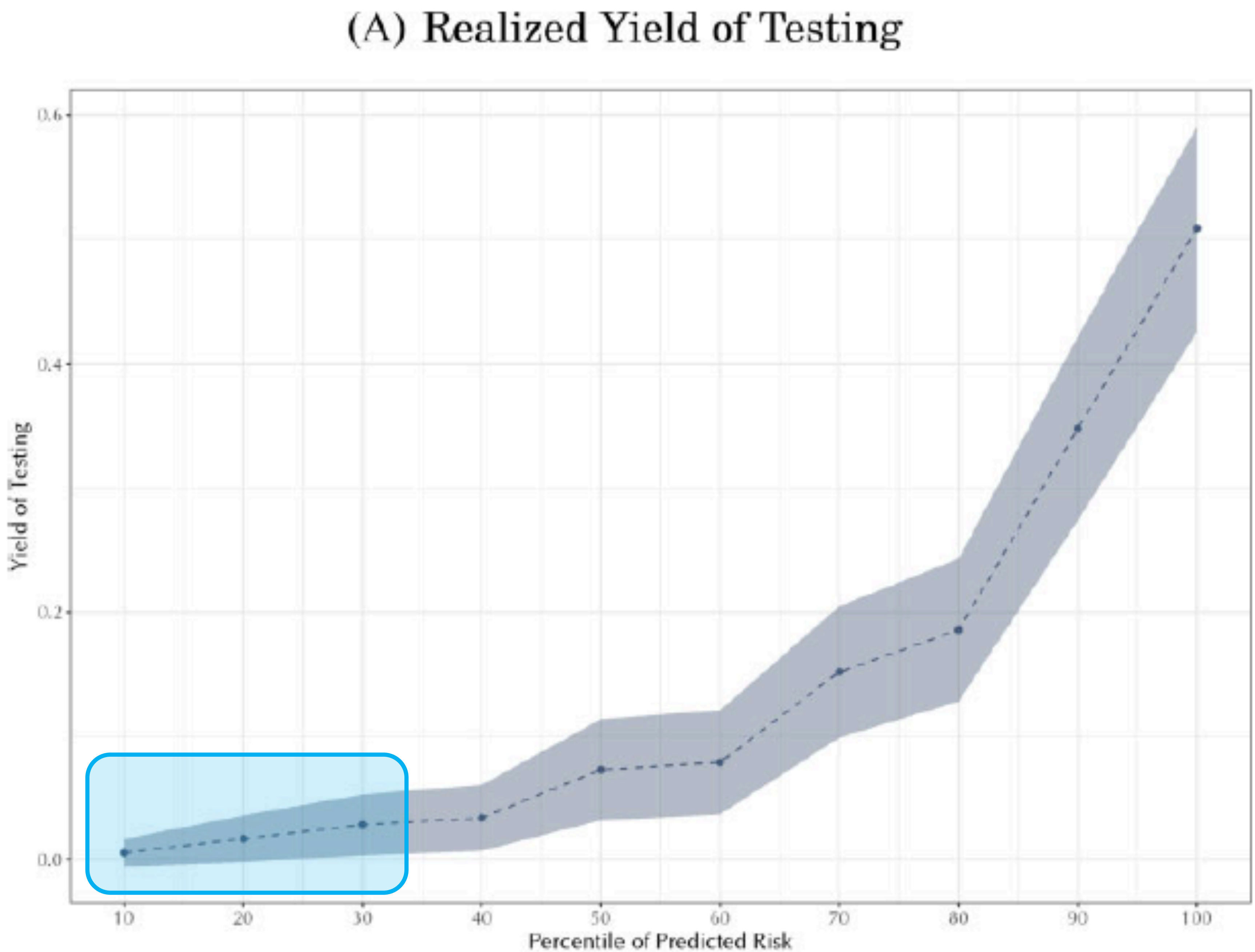
Summary of machine learning process

1. Collect data and split data into training data and "hold-out" sample

2. Use statistical [machine learning] model to select variables that best predict risk of blockage using the training data

3. Use "hold-out" sample to evaluate model (after training and validation)

Using machine learning to study over-testing and under-testing



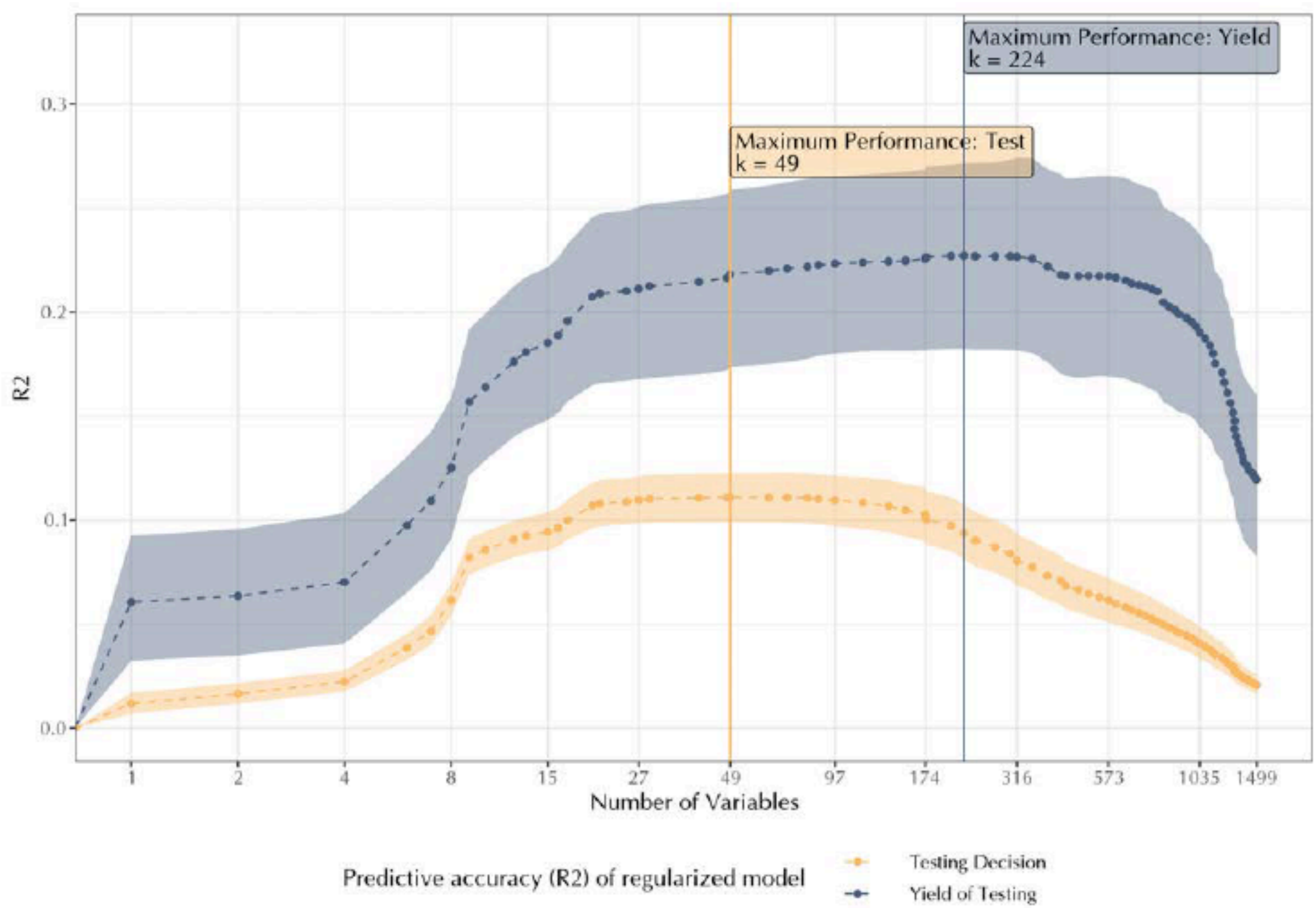
Using machine learning to study over-testing and under-testing

Table 3: Realized Yield, Cost-Effectiveness, and Testing Rate

	Yield Rate (SE) (1)	Cost-Effectiveness ($) (Lower–Upper Bound) (2)	Test Rate (SE) (3)
Full Sample	0.146 (0.004)	89,714 (74,152–113,543)	0.029 (<0.001)
By Risk Bin			
1	0.011 (0.006)	1,352,466 (1,034,814–1,951,515)	0.012 (<0.001)
2	0.036 (0.01)	318,603 (257,296–418,265)	0.017 (0.001)
3	0.07 (0.014)	192,482 (157,552–247,314)	0.047 (0.002)
4	0.168 (0.02)	114,146 (94,154–144,914)	0.088 (0.004)
5	0.429 (0.026)	46,017 (38,178–57,907)	0.383 (0.016)

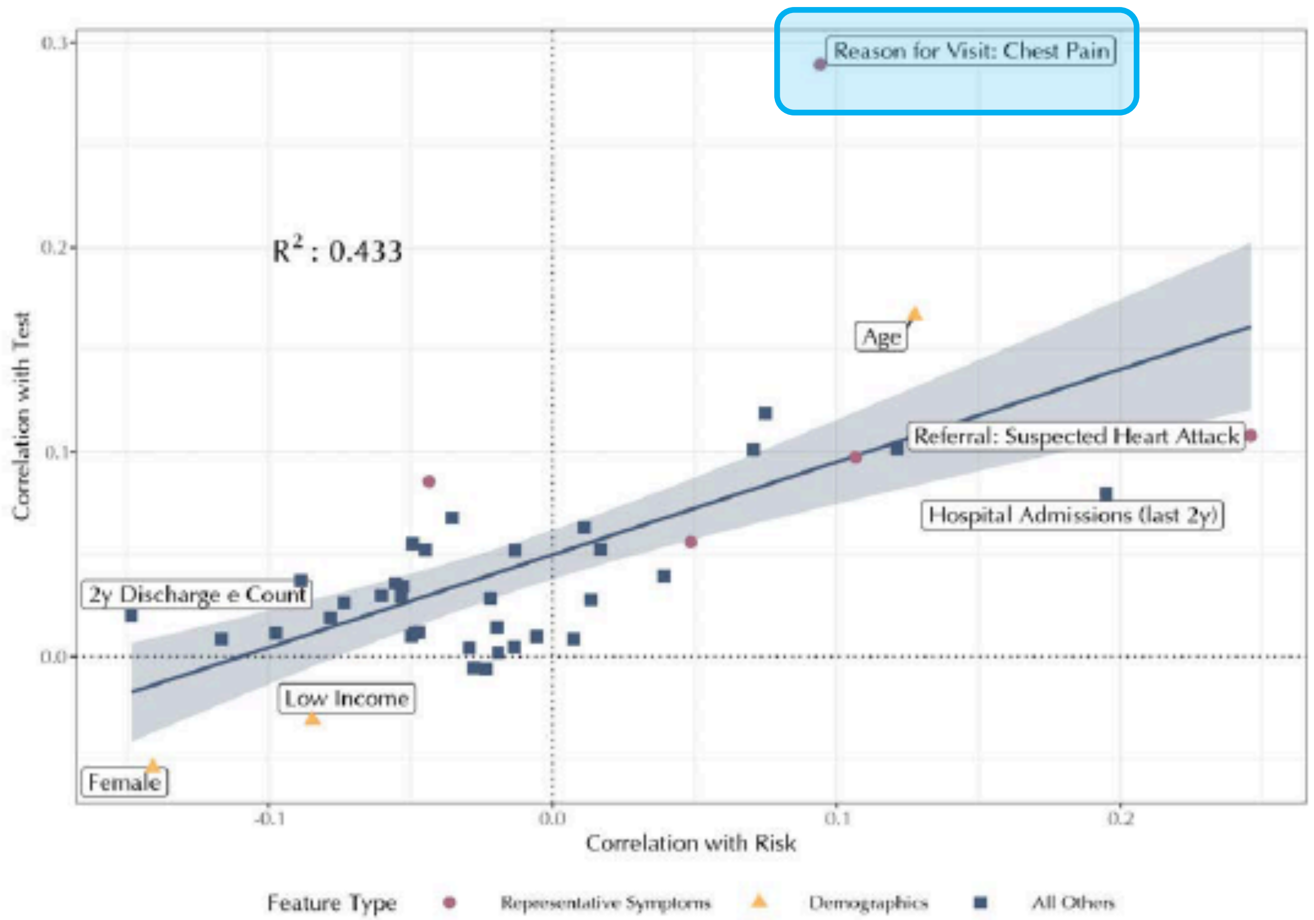
Doctors' decisions are based on a "sparse" model compared to the machine learning algorithm

Figure 5: Explanatory Power of Simple vs. Complex Models of Risk



Doctors' decisions put too much weight on salient symptoms like "chest pain"

Figure 6: Simple Risk Variables: Correlation with Testing and Predicted Risk



Notes: For the simple risk model (with complexity $k = 49$) that best predicts physicians' testing decisions, we show univariate correlations of each included variable with the physician's testing decision (y-axis) and patient risk (x-axis). Each point is one of the 49 included variables, with separate shapes denoting different categories of inputs. Some outlier points of interest are labeled.

Using machine learning to study over-testing and under-testing

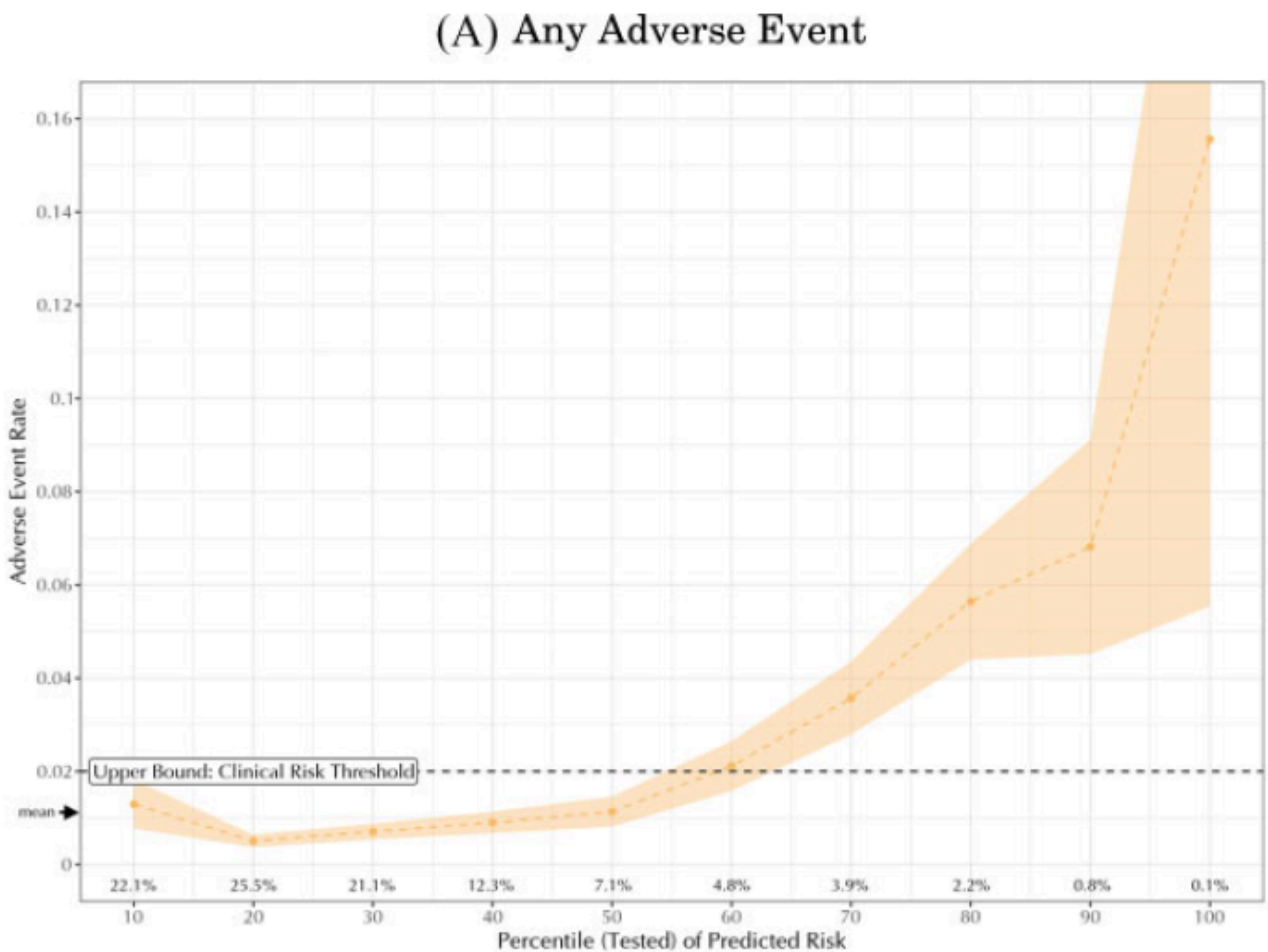
1. Mullainathan and Obermeyer (2021) present very convincing evidence that many stress tests and cardiac catheterizations are simple unnecessary (**over-testing**)

    In many cases, a machine learning algorithm can predict negative test result with a very high degree of accuracy

2. It looks like doctors put too much weight on salient symptoms like "chest pain", which are not very predictive without other indications of blockage

3. Angiograms are very accurate, but they are very expensive. Using a machine learning algorithm to recommend against testing when the expected yield is very very low can achieve large amount of savings at negligible risk

Using machine learning to study over-testing and under-testing



Using machine learning to study over-testing and under-testing

1. Mullainathan and Obermeyer also find evidence of **under-testing**: their machine learning algorithm identifies patients with high predicted risk of blockage but get no ECG, no troponin, no CTCA

2. This "unsuspected and untested" group ends up having adverse events at a "too high" rate; i.e., much more likely to have adverse events within 30 days such as later diagnosis of blockage, arrhythmia, and even death

3. Bottom line: overall, doctors do pretty well making high-stakes testing decisions and treatment decisions in real time, but there may be cases where expert software systems (e.g., machine learning algorithms) can help "nudge" doctors to make even better choices

4. Figuring out how to combine best of both worlds is the "work of the future"

Preparing for the work of the future

Finally, an important issue in the realm of machine–human interactions concerns the unintended loss of human expertise or experience when workers become distanced from a highly specialized task as a result of increased reliance on automated controls. Mindell (2015) discusses an airplane crash that was caused by pure pilot error. In that particular incident, recovery would have been possible using old techniques, but many pilots have been trained in an environment where machines do most of the work, and thus may have difficulty implementing emergency solutions without recourse to automated systems. Beane (2018) reports that medical students are increasingly taught to master robotic surgical techniques at the expense of generalist training. Beane faults the rise of surgical robots for clogging the traditional apprenticeship pipeline. Similarly vivid examples may exist in other professions. As machines play a larger role in many complex and high-stakes tasks, there is a need for further experimentation to learn how best to aid humans in their tasks without distancing them from the underlying processes and considerations involved. Opportunities to redesign workplace practices or training curricula in ways that avoid or minimize the negative consequences of "automation dependency" present an exciting area for new research and experimentation.

Source: https://www.povertyactionlab.org/sites/default/files/documents/work-of-the-future-literature-review-4.2.19.pdf

ACOG clinical guidelines

Having certain factors increases your chances of getting preeclampsia.
Complete this checklist and take it to your pregnancy care provider.

Do you have any of these *HIGH-RISK* factors?

- ❑ I had preeclampsia in a prior pregnancy.
- ❑ I'm having twins, triplets, or more.
- ❑ I have high blood pressure.
- ❑ I have diabetes (type 1 or type 2).
- ❑ I have kidney disease.
- ❑ I have an autoimmune disorder (lupus, antiphospholipid disorder).

Do you have any of these *MODERATE-RISK* factors?

- ❑ This will be my first child.
- ❑ I will be 35 years or older when my baby is born.
- ❑ I am obese [body mass index (BMI) is 30 or more].*
- ❑ This is an IVF pregnancy.
- ❑ I am African American or have African or Afro-Caribbean ancestry.
- ❑ My mother or sister had preeclampsia during pregnancy.
- ❑ I have had a previous pregnancy and the most recent was more than 10 years ago.
- ❑ I had a previous child who weighed less than 5½ pounds (2.5 kg) at birth.
- ❑ I weighed less than 5½ pounds (2.5 kg) when I was born.
- ❑ I have a challenging financial, social, or personal situation.

* A BMI calculator can be found online at CDC.gov.

If you checked ONE OR MORE of these boxes (high-risk) • • • ▶ **Talk to your pregnancy care provider about starting low-dose aspirin to reduce your risk.** ◀ • • • **If you checked TWO OR MORE of these boxes** (moderate-risk)

ACOG clinical guidelines

Having certain factors increases your chances of getting preeclampsia.
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- ❑ I'm having twins, triplets, or more.
- ❑ I have high blood pressure.
- ❑ I have diabetes (type 1 or type 2).
- ❑ I have kidney disease.
- ❑ I have an autoimmune disorder (lupus, antiphospholipid disorder).

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- ❑ I am obese [body mass index (BMI) is 30 or more].*
- ❑ This is an IVF pregnancy.
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- ❑ I had a previous child who weighed less than 5½ pounds (2.5 kg) at birth.
- ❑ I weighed less than 5½ pounds (2.5 kg) when I was born.
- ❑ I have a challenging financial, social, or personal situation.

* A BMI calculator can be found online at CDC.gov.

If you checked <u>ONE OR MORE</u> of these boxes • • • ▶ **Talk to your pregnancy care provider about starting low-dose aspirin to reduce your risk.** ◀ • • • **If you checked <u>TWO OR MORE</u> of these boxes**

Conclusions

1. Learning-by-doing can lead to specialization and differences in treatment choices across areas

2. Health economists have applied Roy models (often applied to labor market) to study doctor decision-making (testing decisions, treatment decisions); this has helped distinguish inefficient over-use and under-use from differences in expertise (comparative advantage)

3. More recently, these approaches have been extended to compare doctor decision-making to machine learning models

4. Lots of opportunities for future work figuring out how to get doctors to adopt and trust expert systems and improve machine-human interactions

Decision-making and race (Gentzkow NBER discussion)

Y^*: Potential outcome
D: Decision
R: Race
ν: Agent's information
$p(\nu; R)$: Agent's posterior
X: Observables

Decision-making and race (Gentzkow NBER discussion)

Discrimination: $E[D|Y^*, R = w] - E[D|Y^*, R = b]$

Bias: $E[D|\boldsymbol{p}, R = w] - E[D|\boldsymbol{p}, R = b]$

Race blindness: $E[D|\boldsymbol{v}, R = w] - E[D|\boldsymbol{v}, R = b]$

Decision-making and race (Gentzkow NBER discussion)

- Can't in general be both non-discriminatory and unbiased
  - Unbiased rule generally leads to different $E(D|Y^*)$
  - See, e.g., Kleinberg et al. 2017
  - Note that efficient → unbiased

- Can't in general be both unbiased and race-blind
  - $p(\nu, R)$ generally differs by R for given ν

- Hard to be both non-discriminatory and race-blind
  - Unless ν effectively orthogonal to R

Health Gradients
Socioeconomic Disparities
Social Determinants of Health

AEA Continuing Education Program
CLASS #7

Matthew J. Notowidigdo (“Noto”)
David McDaniel Keller Professor of Economics
University of Chicago Booth School of Business
Co-Director, Chicago Booth Healthcare Initiative
Co-Scientific Director, J-PAL North America
Research Associate, National Bureau of Economics Research

Outline

- Health Gradients
- Socioeconomic Disparities
- Social Determinants of Health

Inequality in health outcomes

- Income and education are strongly correlated with health outcomes in the US
- Back in 1980, men in the US with incomes in the top 5 percent lived 25% longer than men with incomes in the bottom 5 percent
- Researchers have observed “**gradients**” between health outcomes and income, wealth, education, and social class in high-income countries all around the world, even in countries with relatively egalitarian healthcare systems like Sweden

Health gradients and health disparities [Gross-Noto book]

Chapter 14:
Health Gradients

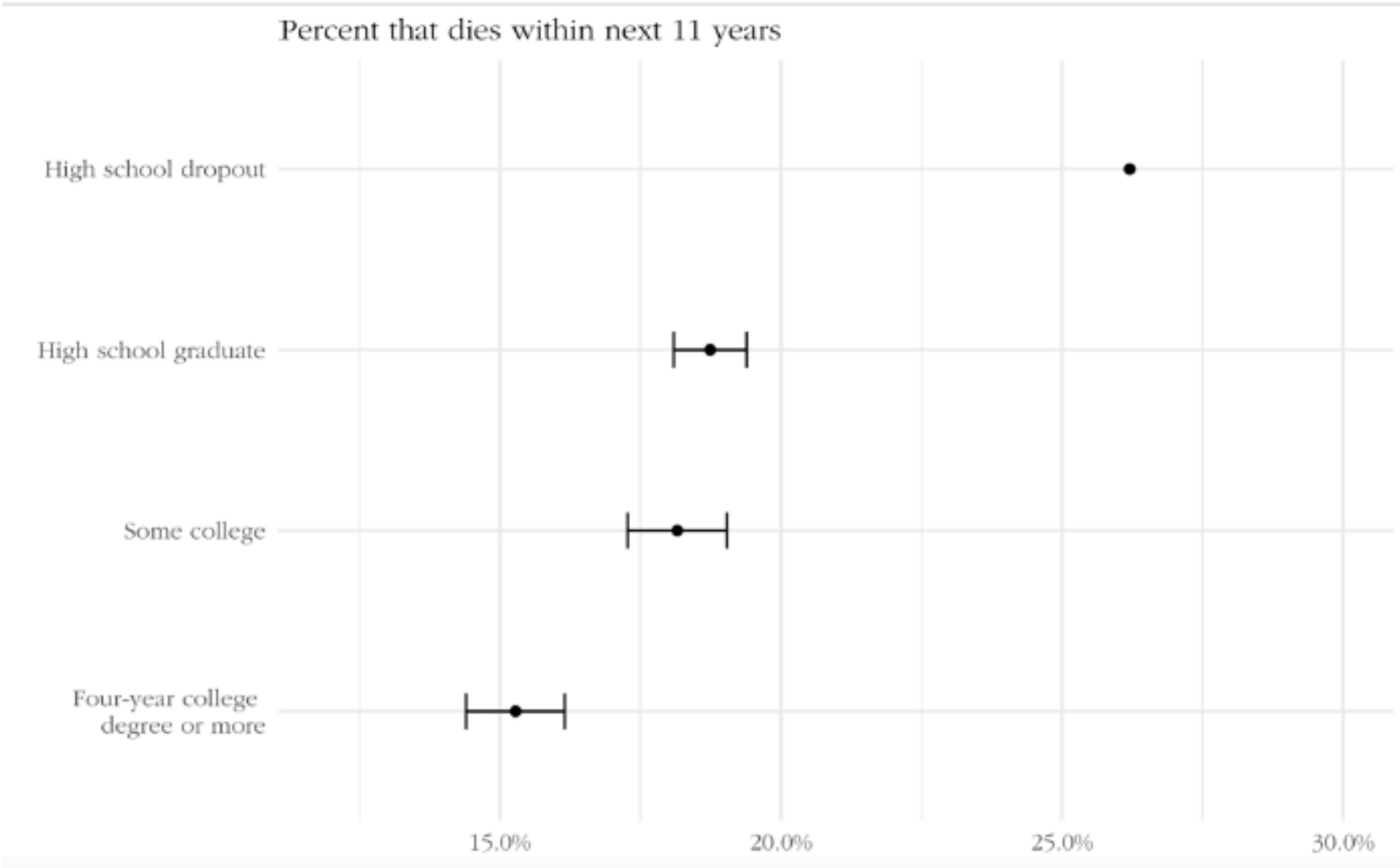
Noto lives near his office at the University of Chicago. The Hyde Park neighborhood is a nice place to live: racially diverse with good schools and little crime. Life expectancy among the residents of Hyde Park is extremely high: nearly 85 years. That's higher than the average life expectancy in every country. And, somehow, the housing is still quite affordable (Robert Wood Johnson Foundation, 2020).

If Noto were to walk a couple miles, though, those numbers change. The Englewood neighborhood, just down the street, is one of the lowest-income neighborhoods in Chicago. Estimated life expectancy there: under 67 years. That's lower than life expectancy in Ethiopia, India, or Indonesia.

That's a difference of 17 years in life expectancy between two close neighborhoods. The 17-year difference is similar to the gap in life expectancy between Japan and Ghana.

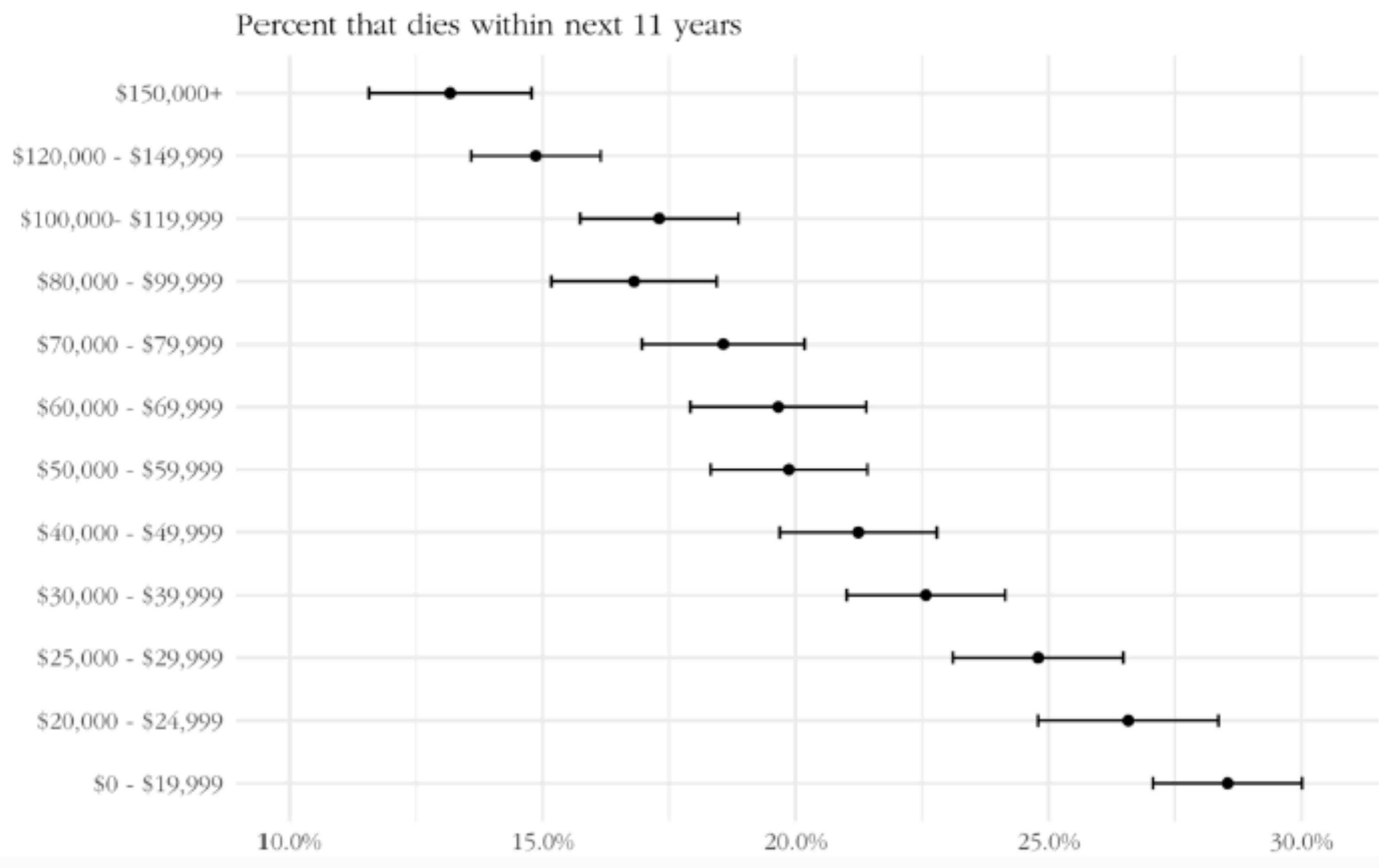
That's two neighborhoods close together on a map, and yet light-years apart on a table of health statistics. How can it be that populations that live so close together face such vastly different health problems?

Health gradients



This figure presents the 11-year mortality rate for American 60–64-year-olds with different levels of education. The "some college" category refers to those who attended college but did not receive a four-year college degree.

Health gradients



This figure presents the 11-year mortality rate for American 60–64-year-olds with different levels of household income.

Health inequality trends

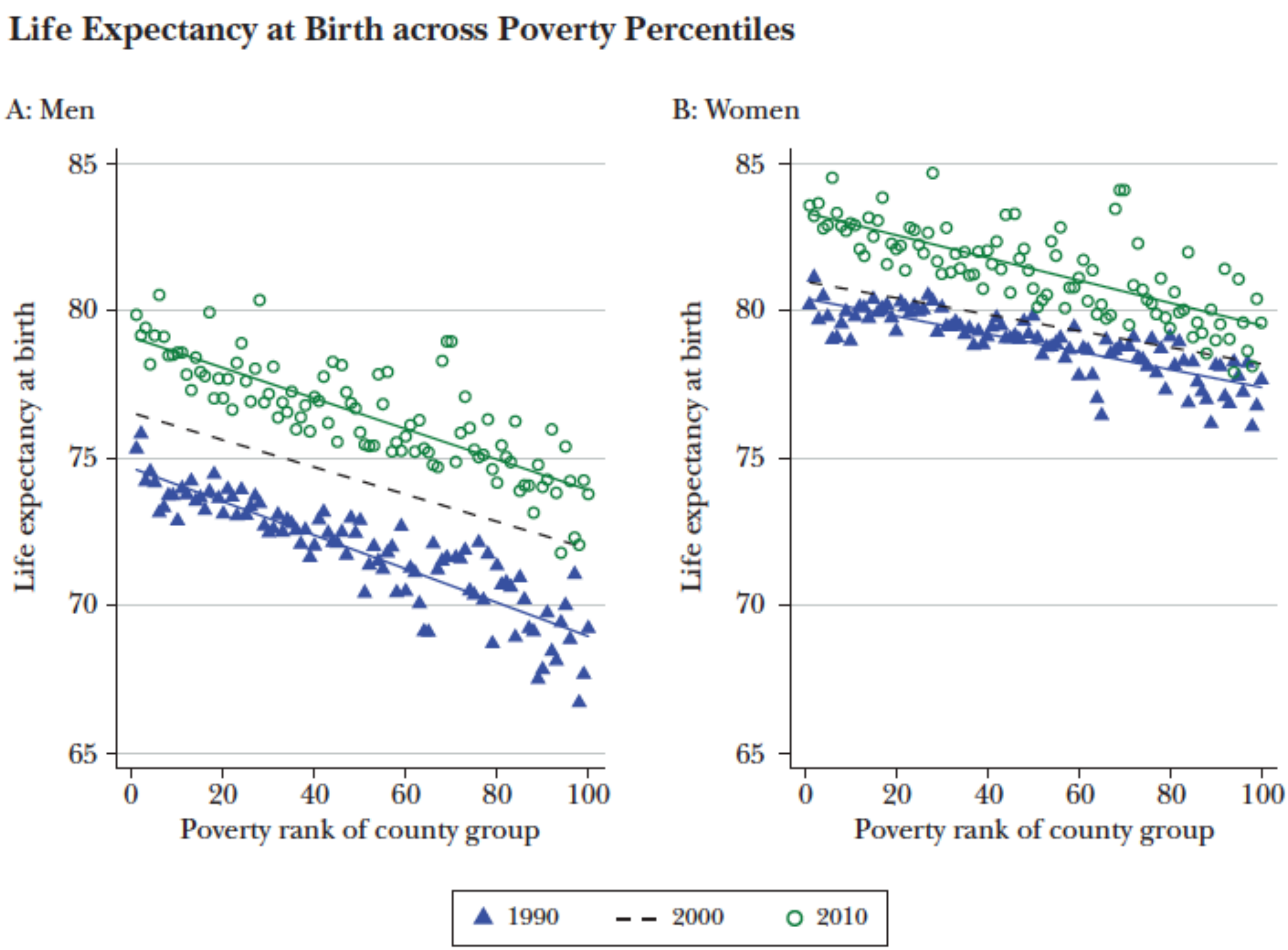
DEMOGRAPHY

Inequality in mortality decreased among the young while increasing for older adults, 1990–2010

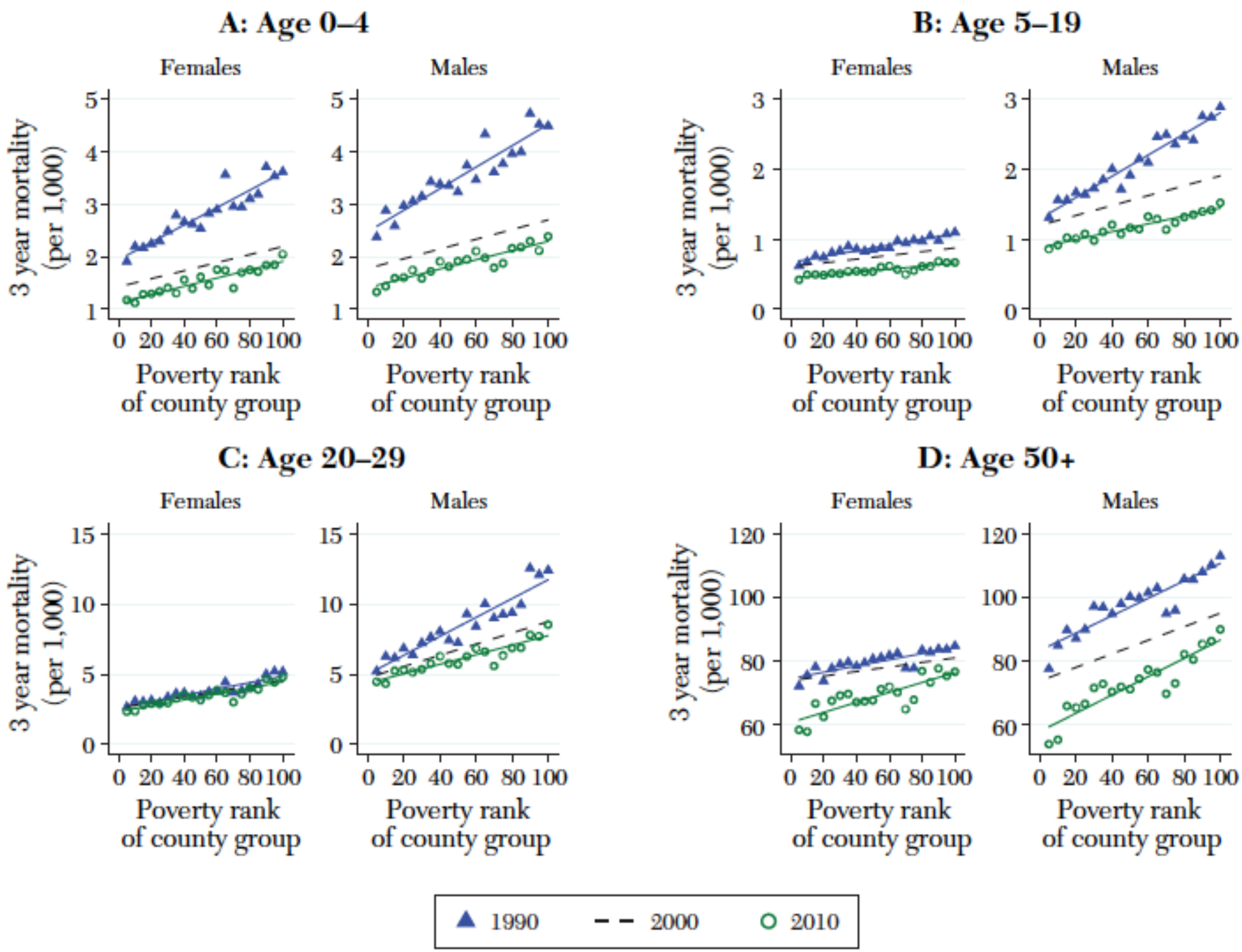
J. Currie[1,2,3*] and H. Schwandt[3,4,5]

Many recent studies point to increasing inequality in mortality in the United States over the past 20 years. These studies often use mortality rates in middle and old age. We used poverty level rankings of groups of U.S. counties as a basis for analyzing inequality in mortality for all age groups in 1990, 2000, and 2010. Consistent with previous studies, we found increasing inequality in mortality at older ages. For children and young adults below age 20, however, we found strong mortality improvements that were most pronounced in poorer counties, implying a strong decrease in mortality inequality. These younger cohorts will form the future adult U.S. population, so this research suggests that inequality in old-age mortality is likely to decline.

Health inequality trends



Health inequality trends



Inequality in mortality between Black and White Americans by age, place, and cause and in comparison to Europe, 1990 to 2018

Although there is a large gap between Black and White American life expectancies, the gap fell 48.9% between 1990 and 2018, mainly due to mortality declines among Black Americans. We examine age-specific mortality trends and racial gaps in life expectancy in high- and low-income US areas and with reference to six European countries. Inequalities in life expectancy are starker in the United States than in Europe. In 1990, White Americans and Europeans in high-income areas had similar overall life expectancy, while life expectancy for White Americans in low-income areas was lower. However, since then, even high-income White Americans have lost ground relative to Europeans. Meanwhile, the gap in life expectancy between Black Americans and Europeans decreased by 8.3%. Black American life expectancy increased more than White American life expectancy in all US areas, but improvements in lower-income areas had the greatest impact on the racial life expectancy gap. The causes that contributed the most to Black Americans' mortality reductions included cancer, homicide, HIV, and causes originating in the fetal or infant period. Life expectancy for both Black and White Americans plateaued or slightly declined after 2012, but this stalling was most evident among Black Americans even prior to the COVID-19 pandemic. If improvements had continued at the 1990 to 2012 rate, the racial gap in life expectancy would have closed by 2036. European life expectancy also stalled after 2014. Still, the comparison with Europe suggests that mortality rates of both Black and White Americans could fall much further across all ages and in both high-income and low-income areas.

Black-White differences in mortality rates

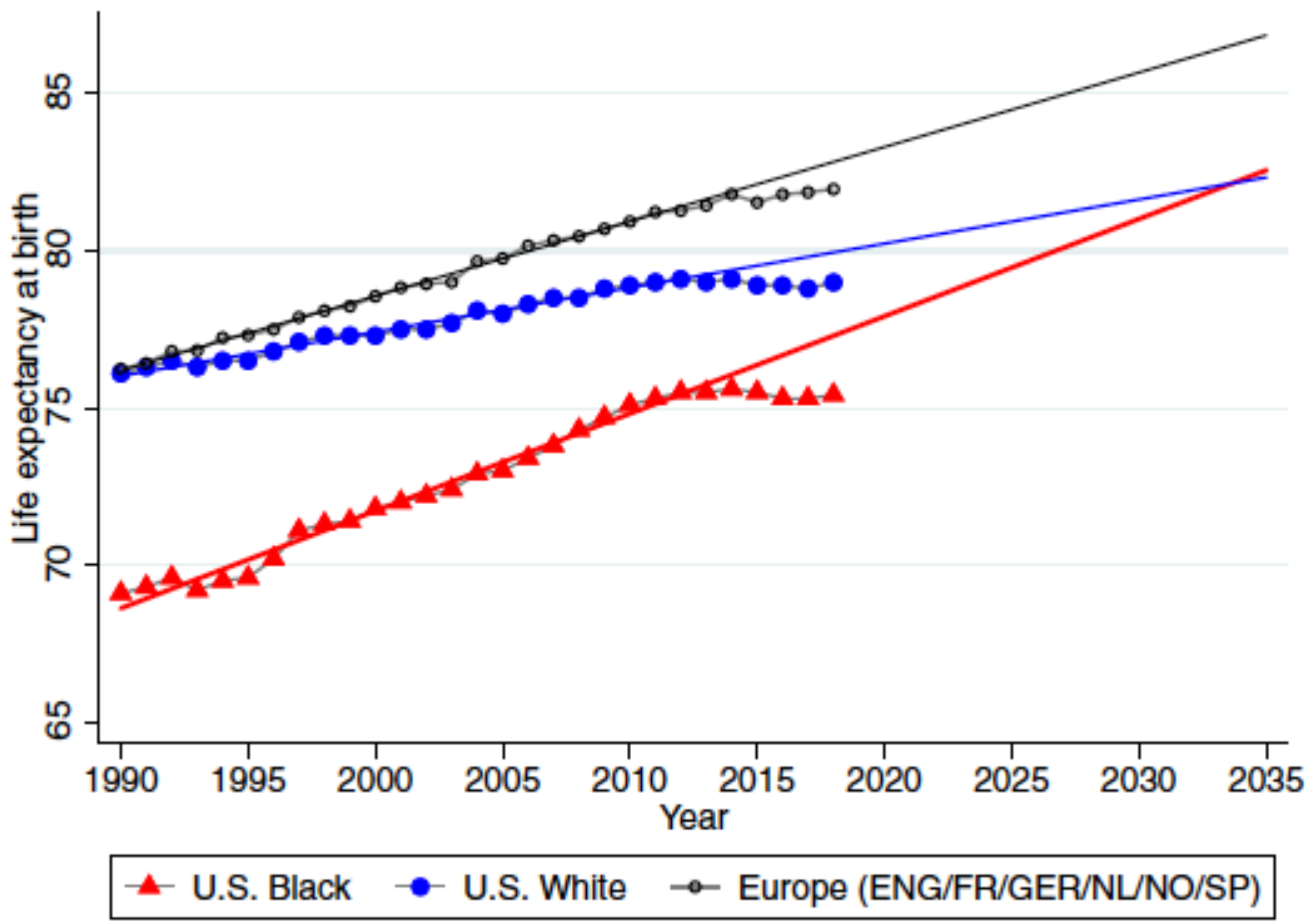
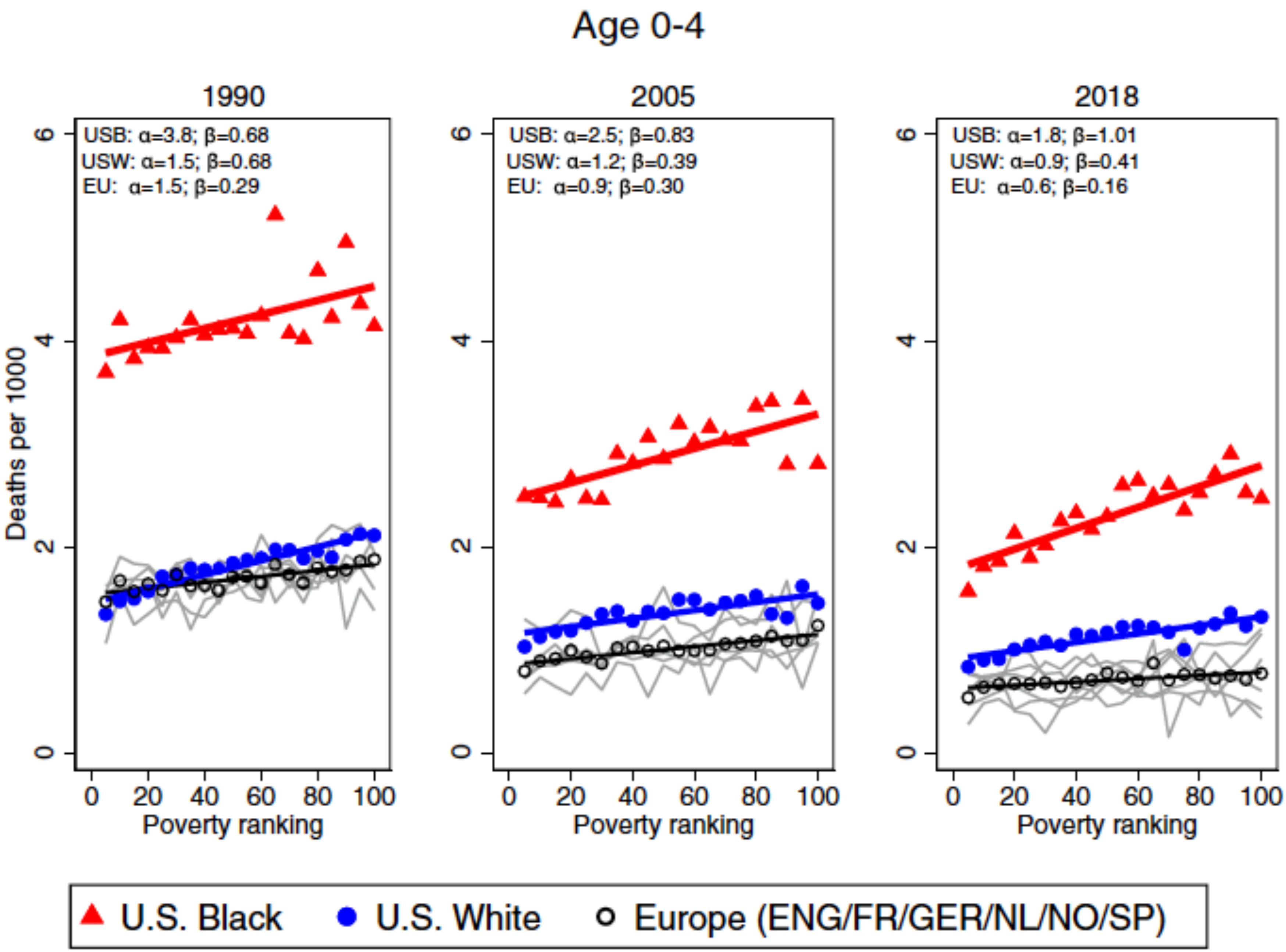
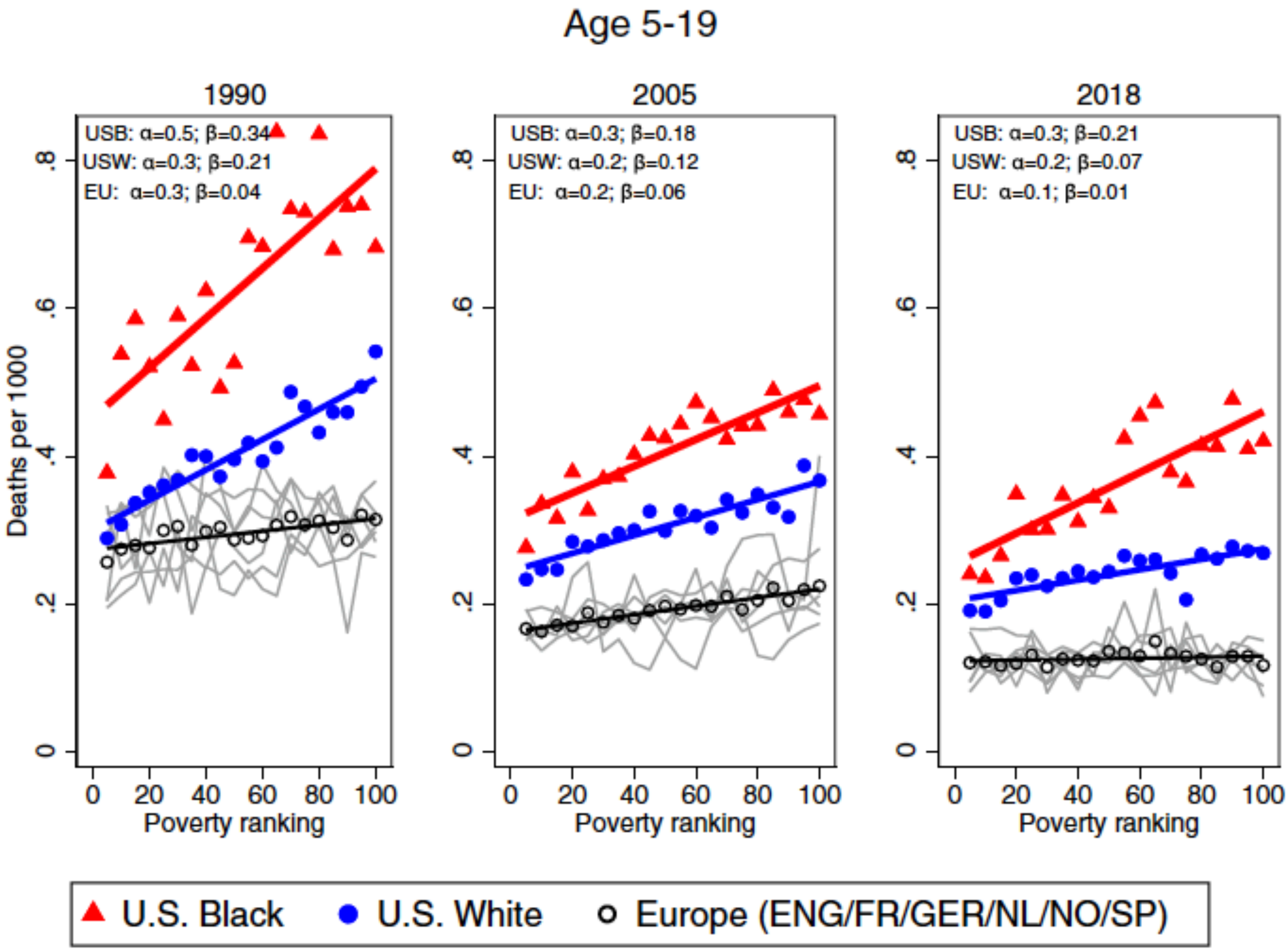


Fig. 5. Life expectancy for Black Americans, White Americans, and six European countries, extrapolated to 2035 fitting a linear trend through 1990 to 2012. Black American, White American, and European life expectancies are plotted over time and extrapolated to 2035 using a linear trend through 1990 to 2012. Black circles show the population weighted average life expectancy across England, France, Germany, the Netherlands, Norway, and Spain.

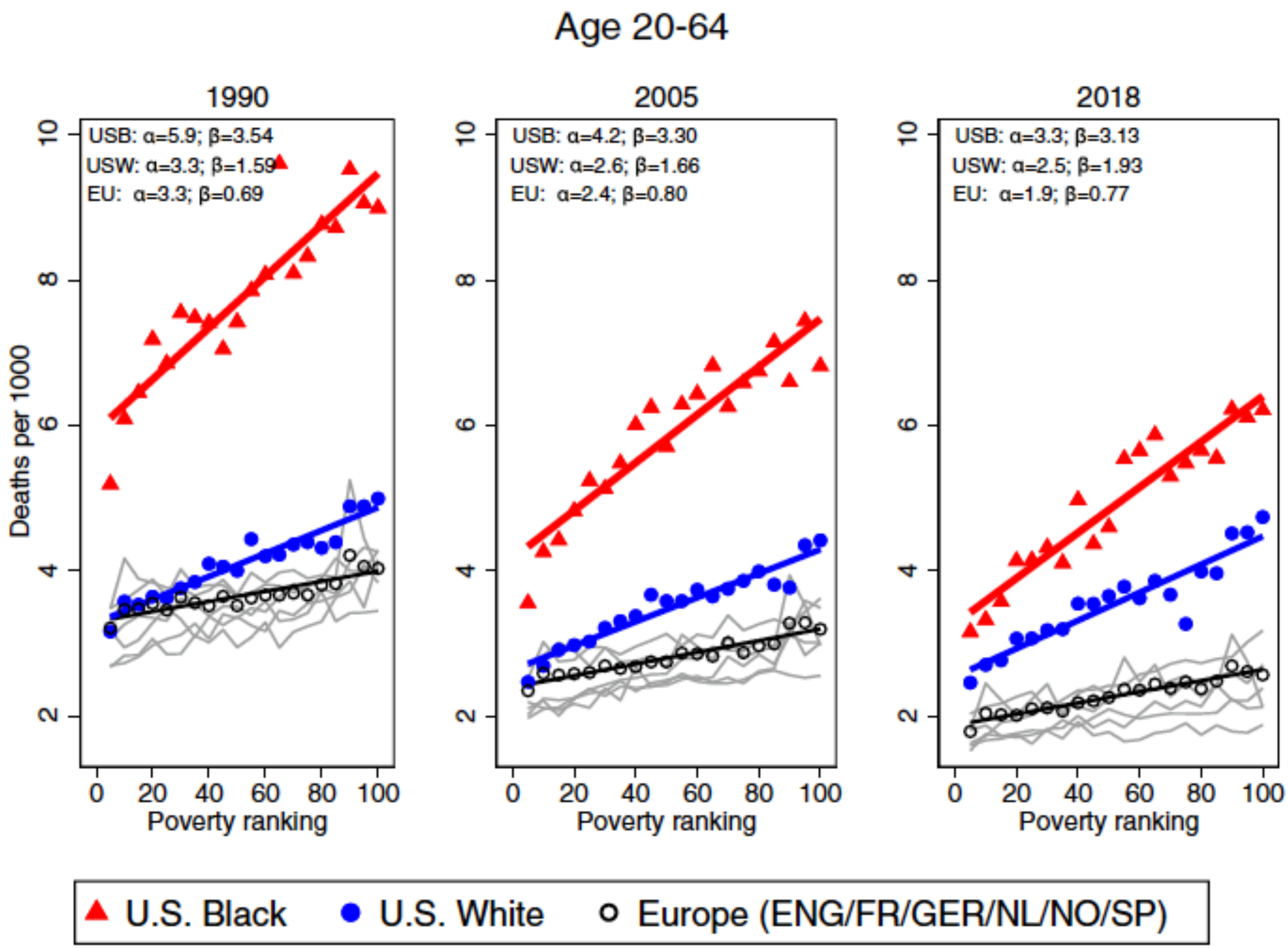
Black-White differences in mortality rates



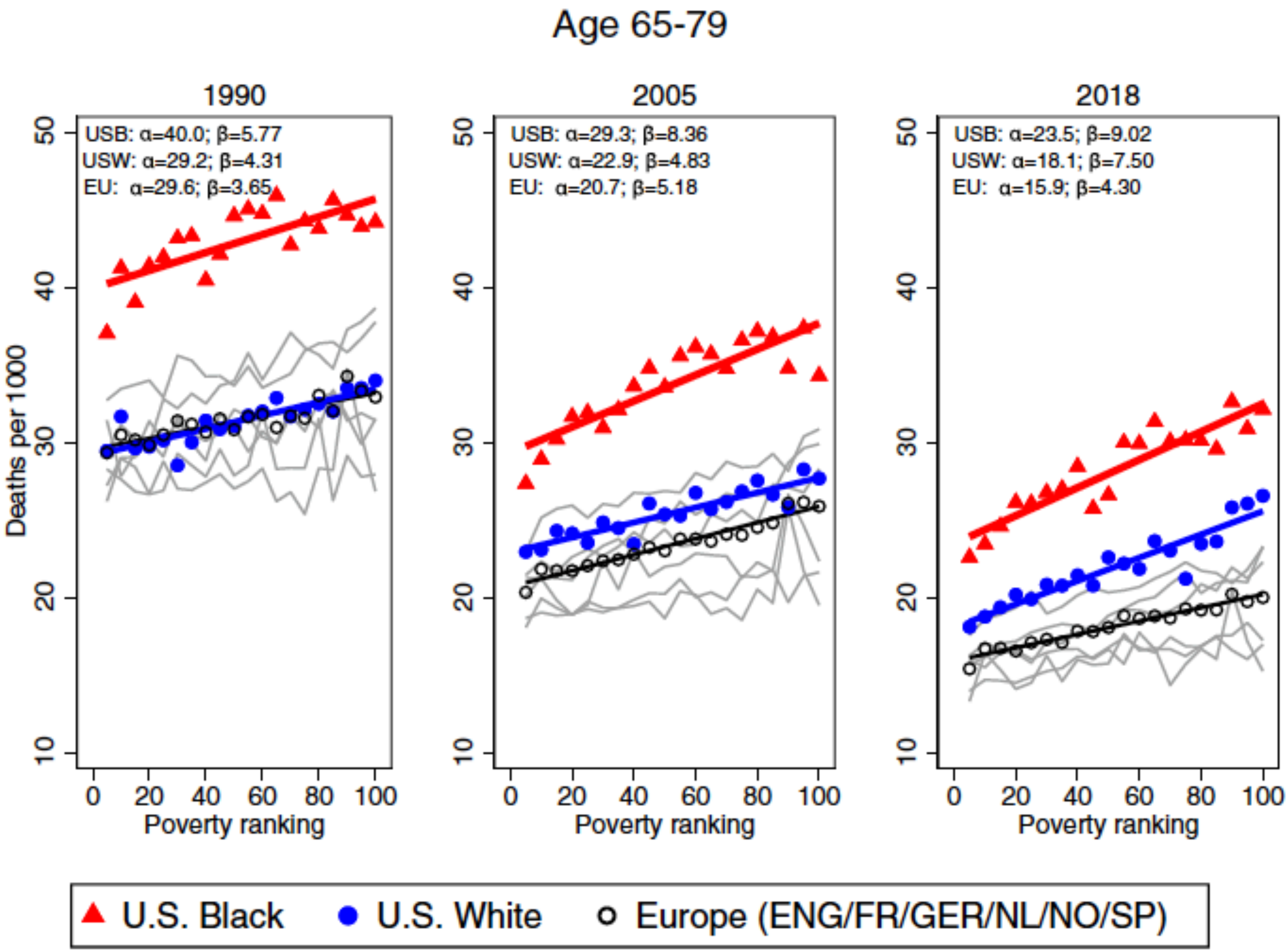
Black-White differences in mortality rates



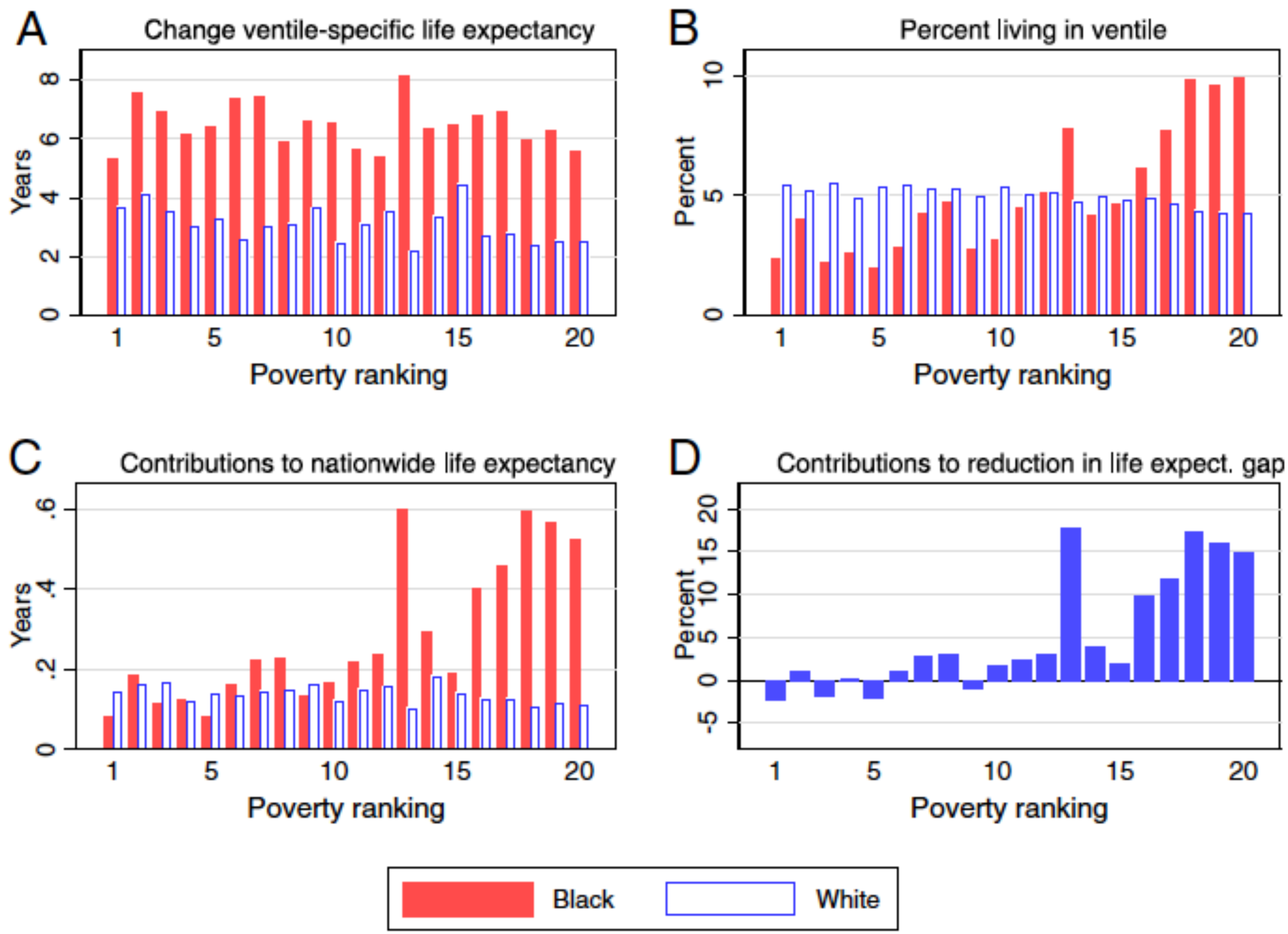
Black-White differences in mortality rates



Black-White differences in mortality rates

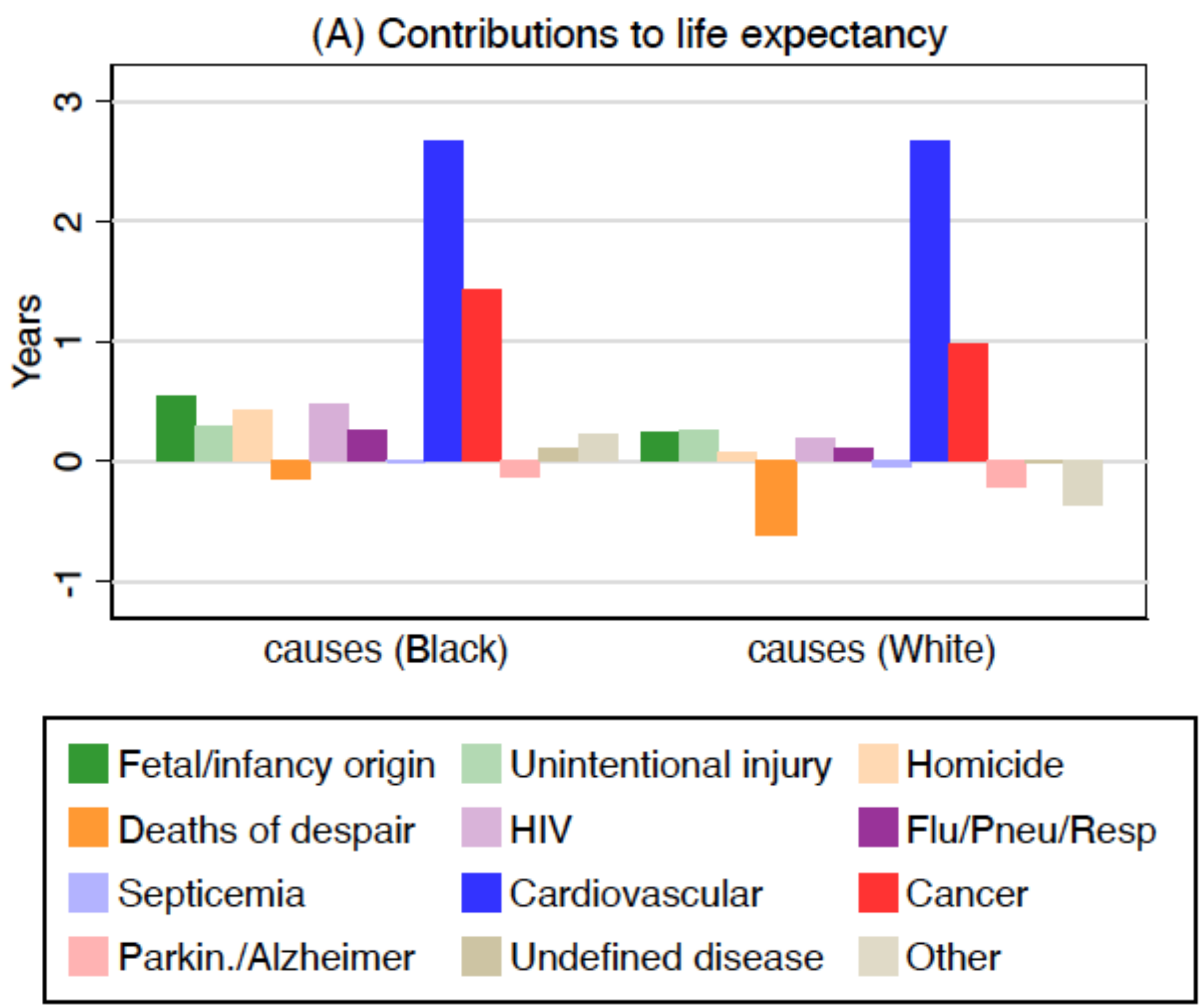


Black-White differences in mortality rates



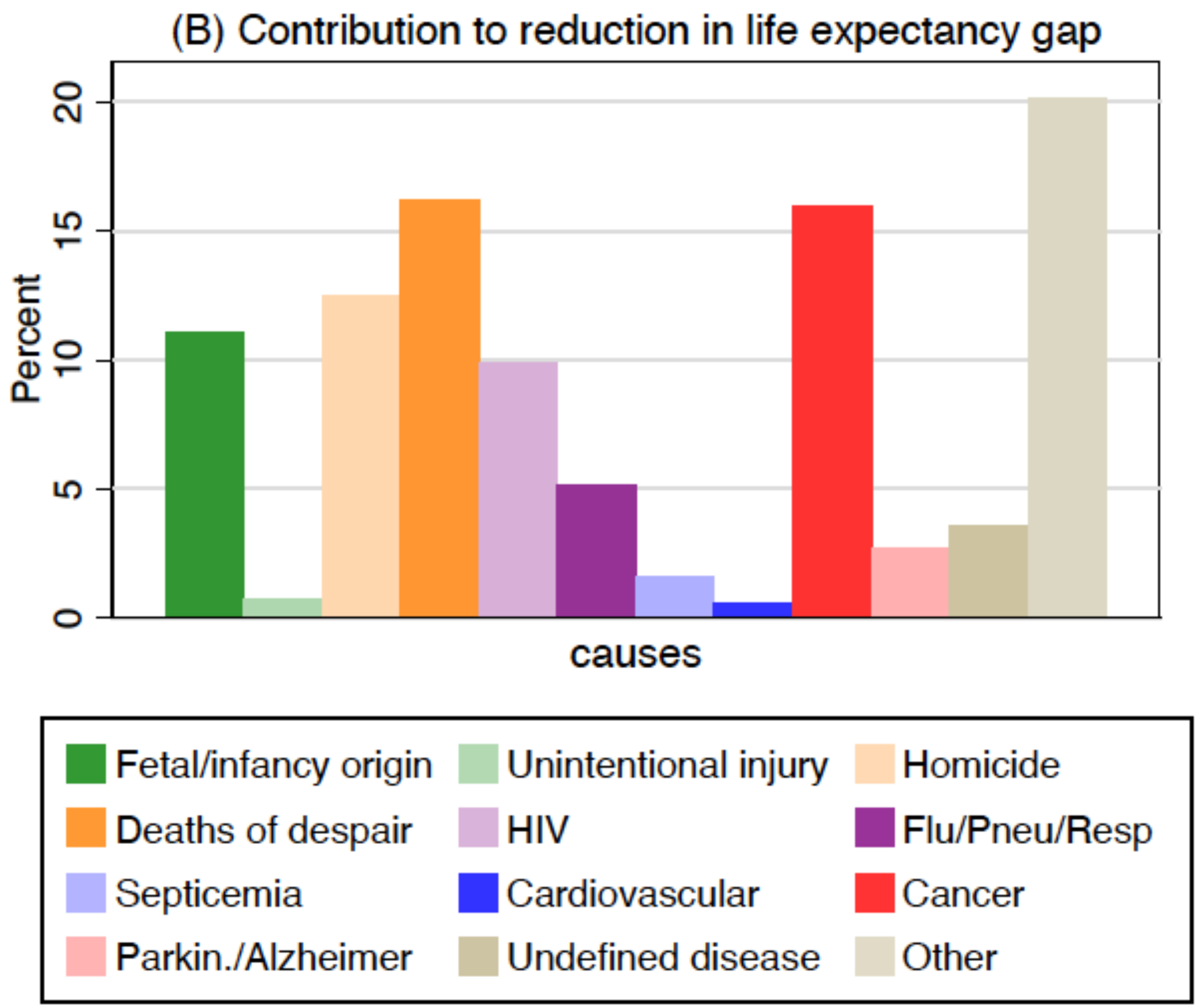
Black-White differences in mortality rates

Figure S1: Cause-specific contributions to life expectancy gains and to the reduction of the Black-White life expectancy gap, 1990-2018



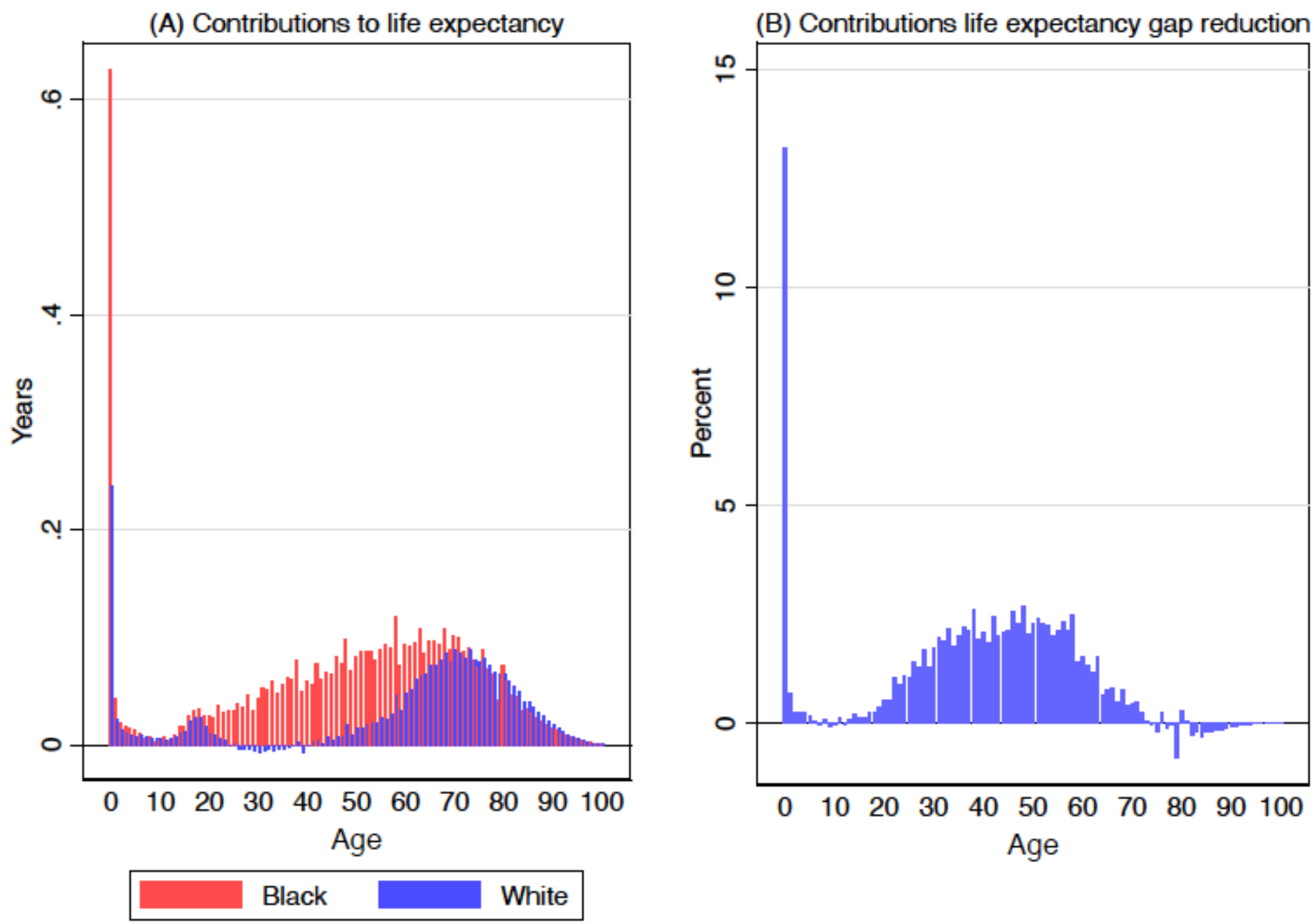
Black-White differences in mortality rates

Figure S1: Cause-specific contributions to life expectancy gains and to the reduction of the Black-White life expectancy gap, 1990-2018



Black-White differences in mortality rates

Figure S3: Age-specific contributions to life expectancy gains and to the reduction of the Black-White life expectancy gap, 1990-2018



What causes the health-wealth gradient?

Correlation, or causation? If it's causal, is it the…

- Causal effect of income on health? (e.g., higher incomes lead to better access to health care)
- Causal effect of health on income? (e.g., ability to earn income may be limited by poor health)
- Causal effect of education on health? (e.g., more education provides more information about how to produce good health)
- Causal effect of social status and/or income rank on health? (e.g., higher social status leads to greater "sense of control" which is good for health)
- Result of joint determination of health and wealth through other factors (e.g., parental behaviors jointly affect children's health and income)

Causal Effect of Wealth on Health

WEALTH, HEALTH, AND CHILD DEVELOPMENT: EVIDENCE FROM ADMINISTRATIVE DATA ON SWEDISH LOTTERY PLAYERS*

DAVID CESARINI
ERIK LINDQVIST
ROBERT ÖSTLING
BJÖRN WALLACE

We use administrative data on Swedish lottery players to estimate the causal impact of substantial wealth shocks on players' own health and their children's health and developmental outcomes. Our estimation sample is large, virtually free of attrition, and allows us to control for the factors conditional on which the prizes were randomly assigned. In adults, we find no evidence that wealth impacts mortality or health care utilization, with the possible exception of a small reduction in the consumption of mental health drugs. Our estimates allow us to rule out effects on 10-year mortality one sixth as large as the cross-sectional wealth-mortality gradient. In our intergenerational analyses, we find that wealth increases children's health care utilization in the years following the lottery and may also reduce obesity risk. The effects on most other child outcomes, including drug consumption, scholastic performance, and skills, can usually be bounded to a tight interval around zero. Overall, our findings suggest that in affluent countries with extensive social safety nets, causal effects of wealth are not a major source of the wealth-mortality gradients, nor of the observed relationships between child developmental outcomes and household income. *JEL* Codes: I10, I14, J24.

Causal Effect of Wealth on Health

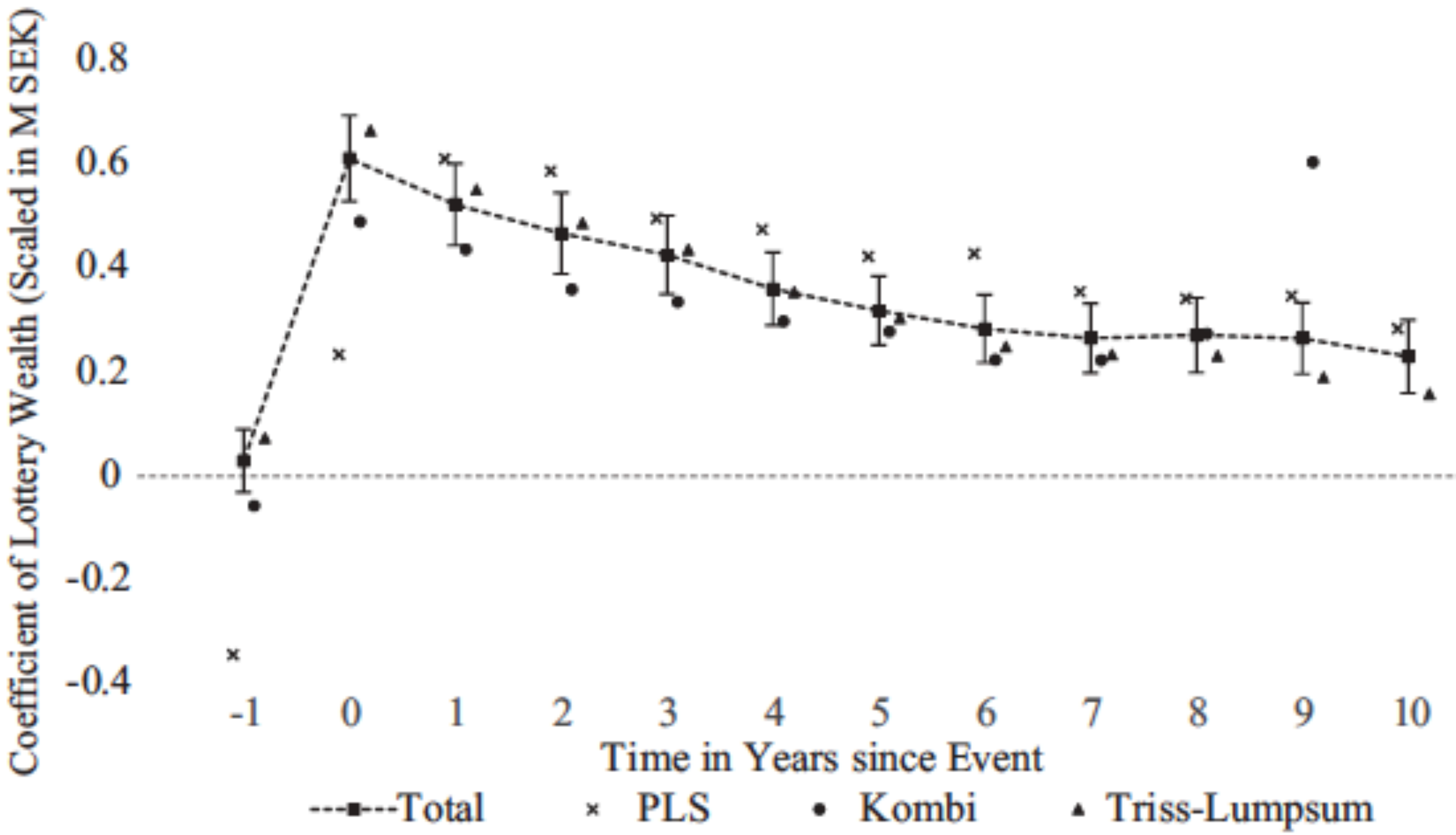


FIGURE I

The Effect of Lottery Wealth on Net Wealth According to Administrative Registers

Causal effect of wealth on health

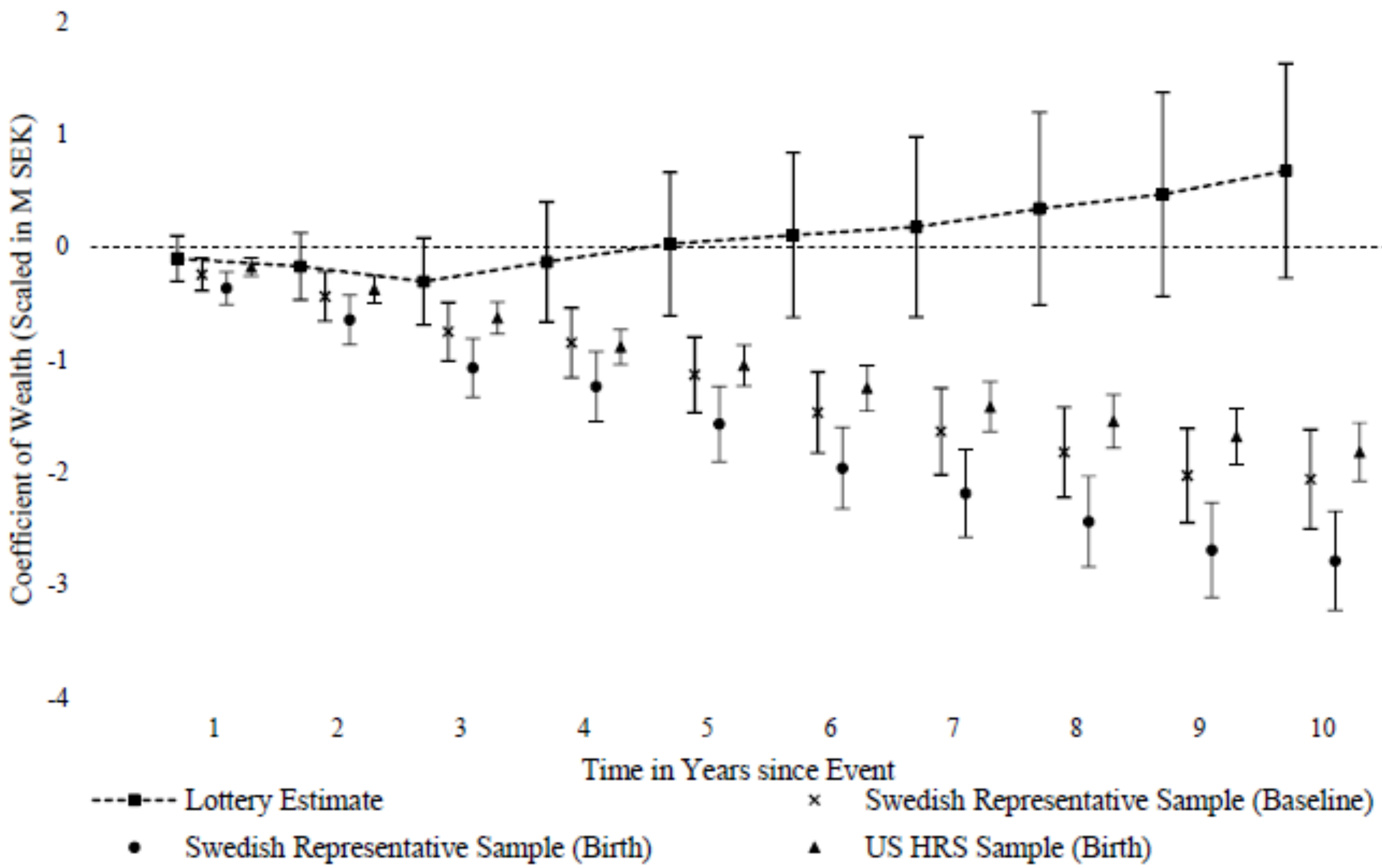


FIGURE II
Wealth and Mortality

This figure contrasts our lottery-based estimates of the effect of wealth on mortality to gradients estimated in Swedish and US population samples. The population samples have been re-weighted to match the sex and age distribution of our sample of lottery winners. Gradients are separately estimated with controls for birth demographics for Sweden and the US, as well as with the full set of baseline controls for Sweden. Standard errors are clustered by individual, and the error bars give 95% confidence intervals of the coefficient.

New perspective on health gradient: Intrafamily expertise

The Roots of Health Inequality and the Value of Intrafamily Expertise

Yiqun Chen

Petra Persson

Maria Polyakova

AMERICAN ECONOMIC JOURNAL: APPLIED ECONOMICS
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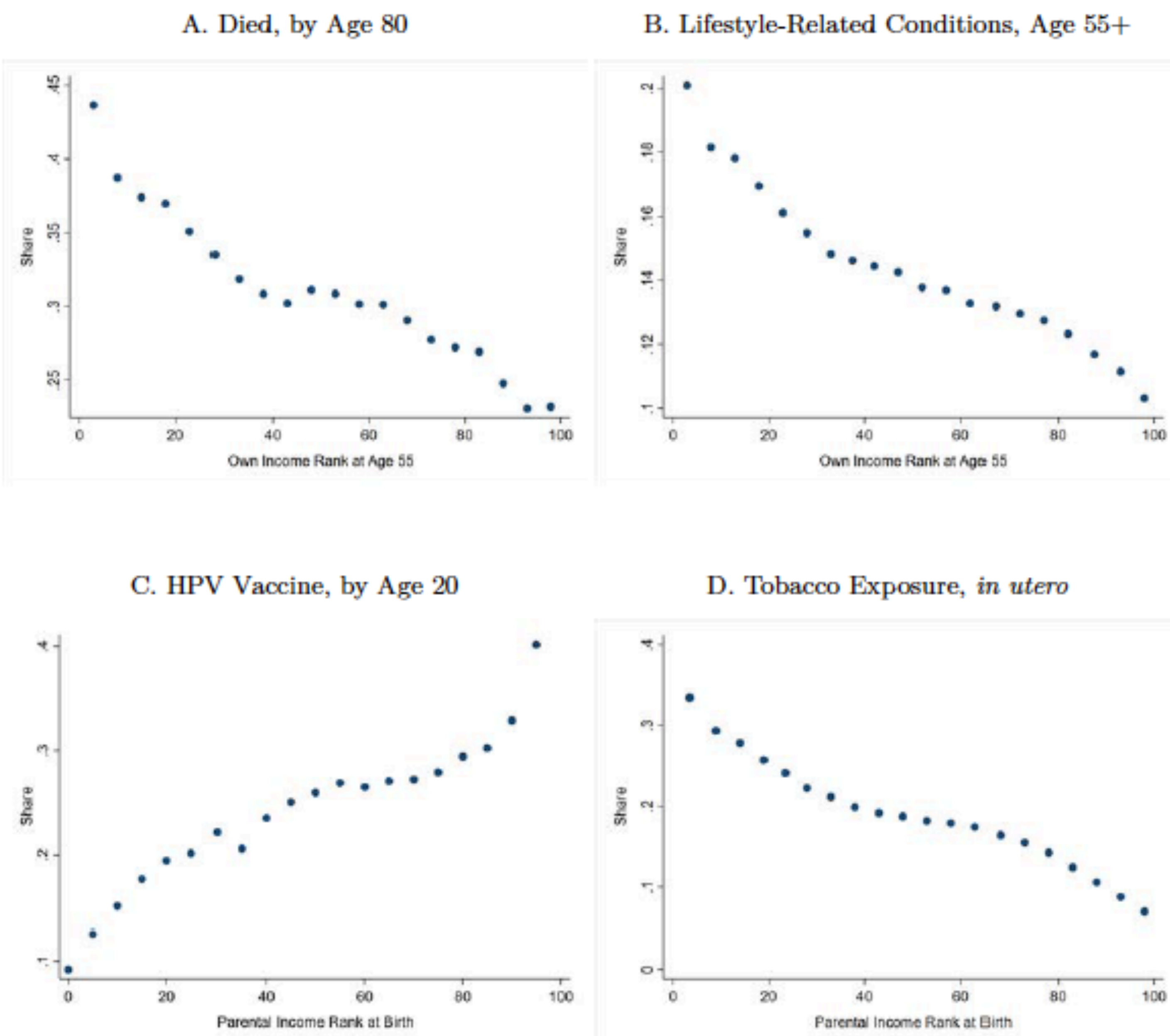
Abstract

In the context of Sweden, we show that having a doctor in the family raises preventive health investments throughout the life cycle, improves physical health, and prolongs life. Two quasi-experimental research designs—medical school admission lotteries and variation in the timing of medical degrees—support a causal interpretation of these effects. A hypothetical policy that would bring the same health behavior changes and benefits to all Swedes would close 18 percent of the mortality-income gradient. Our results suggest that socioeconomic differences in exposure to health-related expertise may meaningfully contribute to health inequality.

Health disparities in Sweden by income rank

Figure 1: Income Gradients in Mortality and Morbidity over the Lifecycle

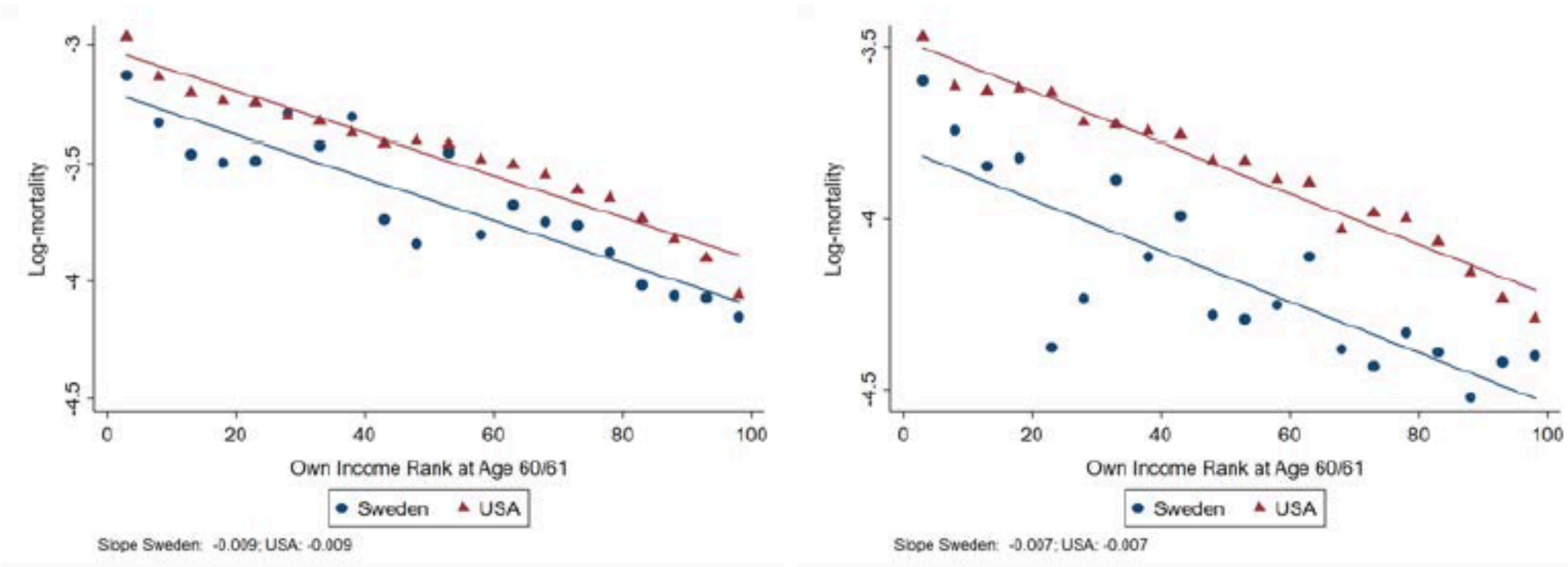


Health disparities: Sweden versus US

Figure 2: Income Gradients in Mortality in the US and Sweden

A. Mortality at Age 75, Men

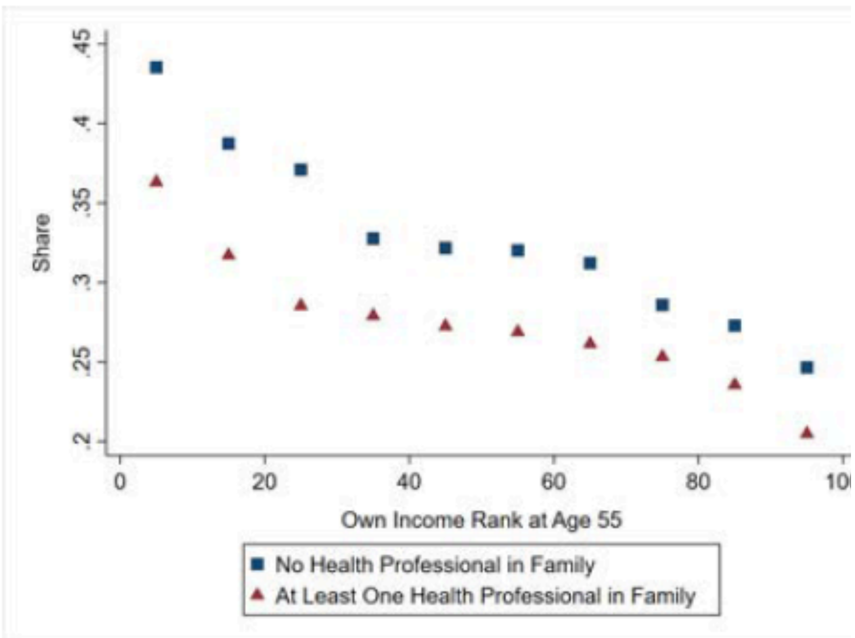
B. Mortality at age 75, Women



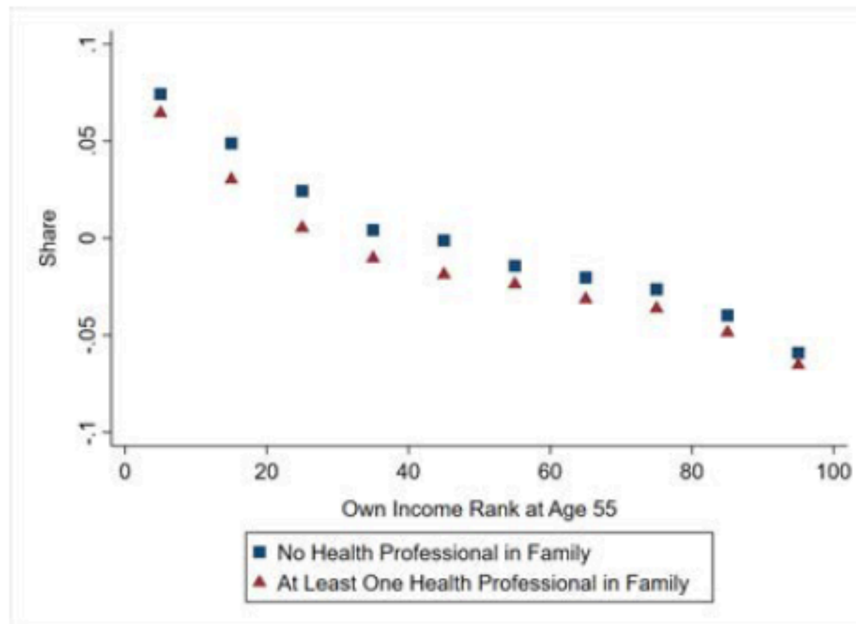
Having a Health Professional in the Family

Figure 3: Health Professional in the Family and Health at Older Ages: Non-Parametric Evidence

A. Died, by Age 80



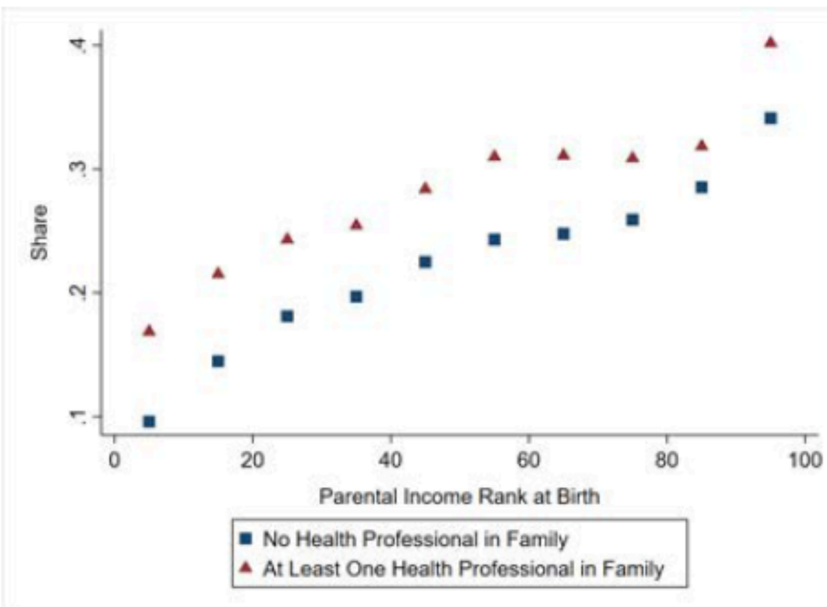
C. Lifestyle-Related Conditions, Age 55+



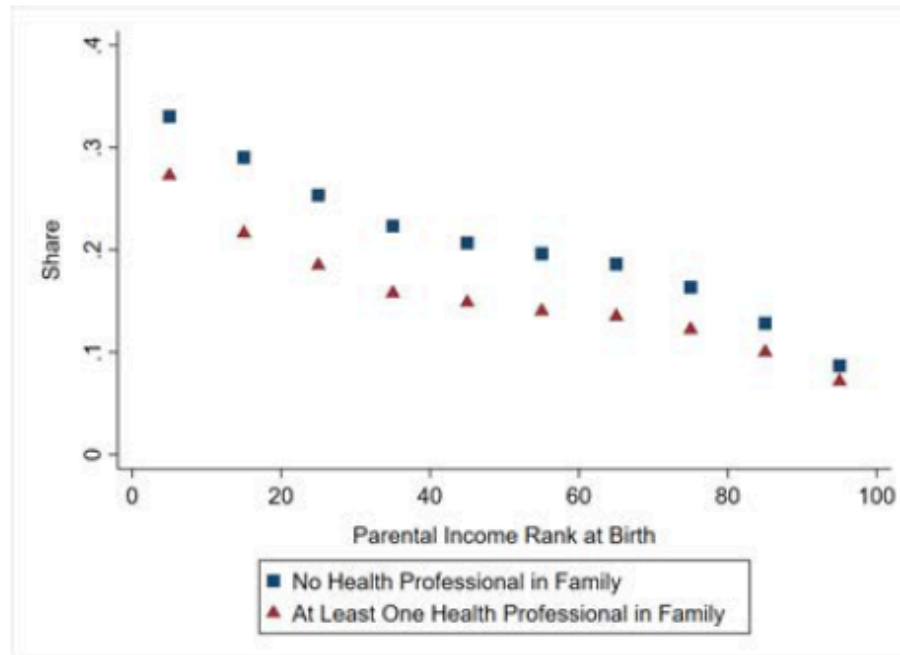
Having a Health Professional in the Family

Figure 4: Health Professional in the Family and Health at Younger Ages: Non-Parametric Evidence

A. HPV Vaccine, by Age 20



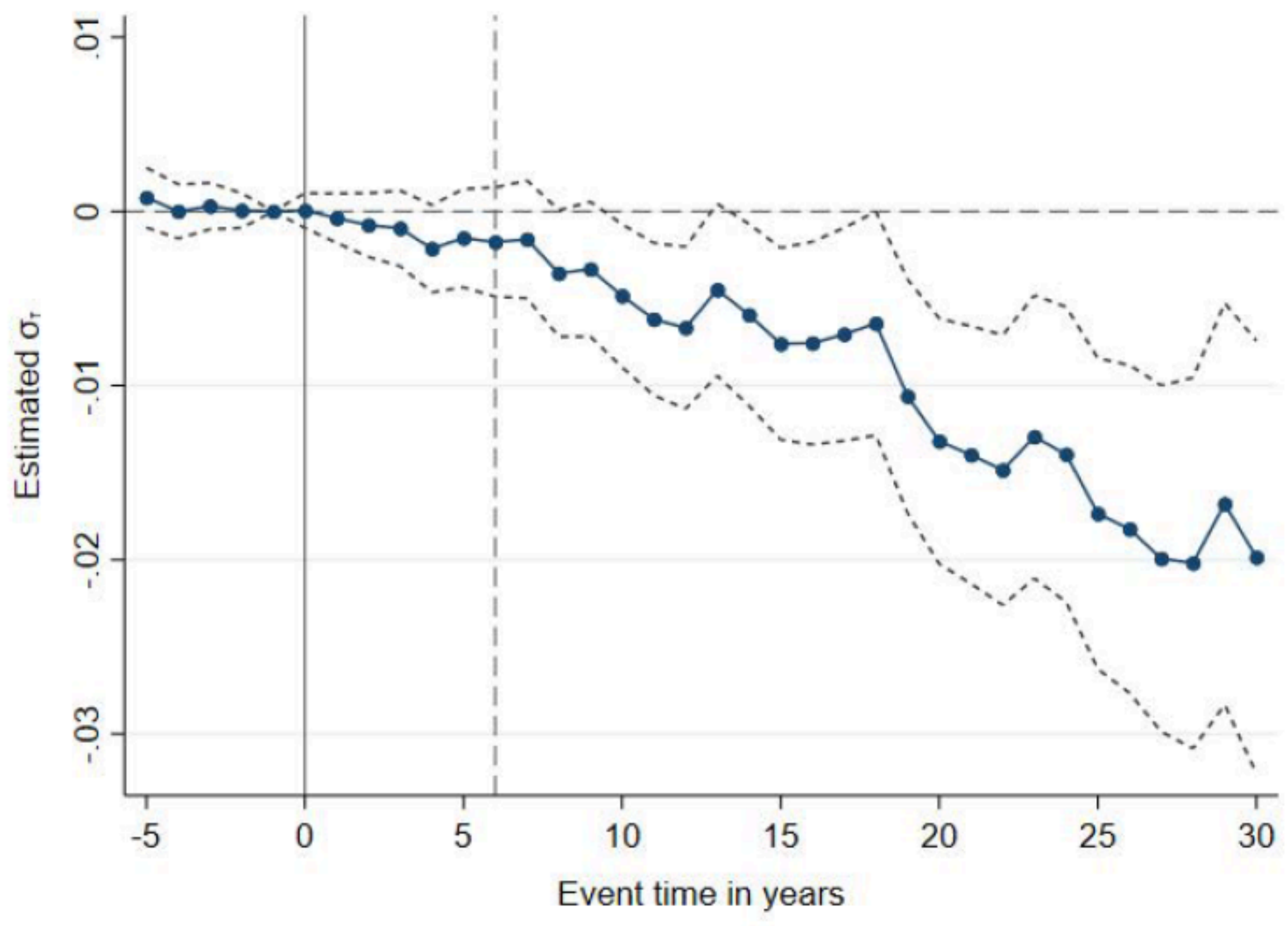
C. Tobacco Exposure, *in utero*



Having a Health Professional in the Family

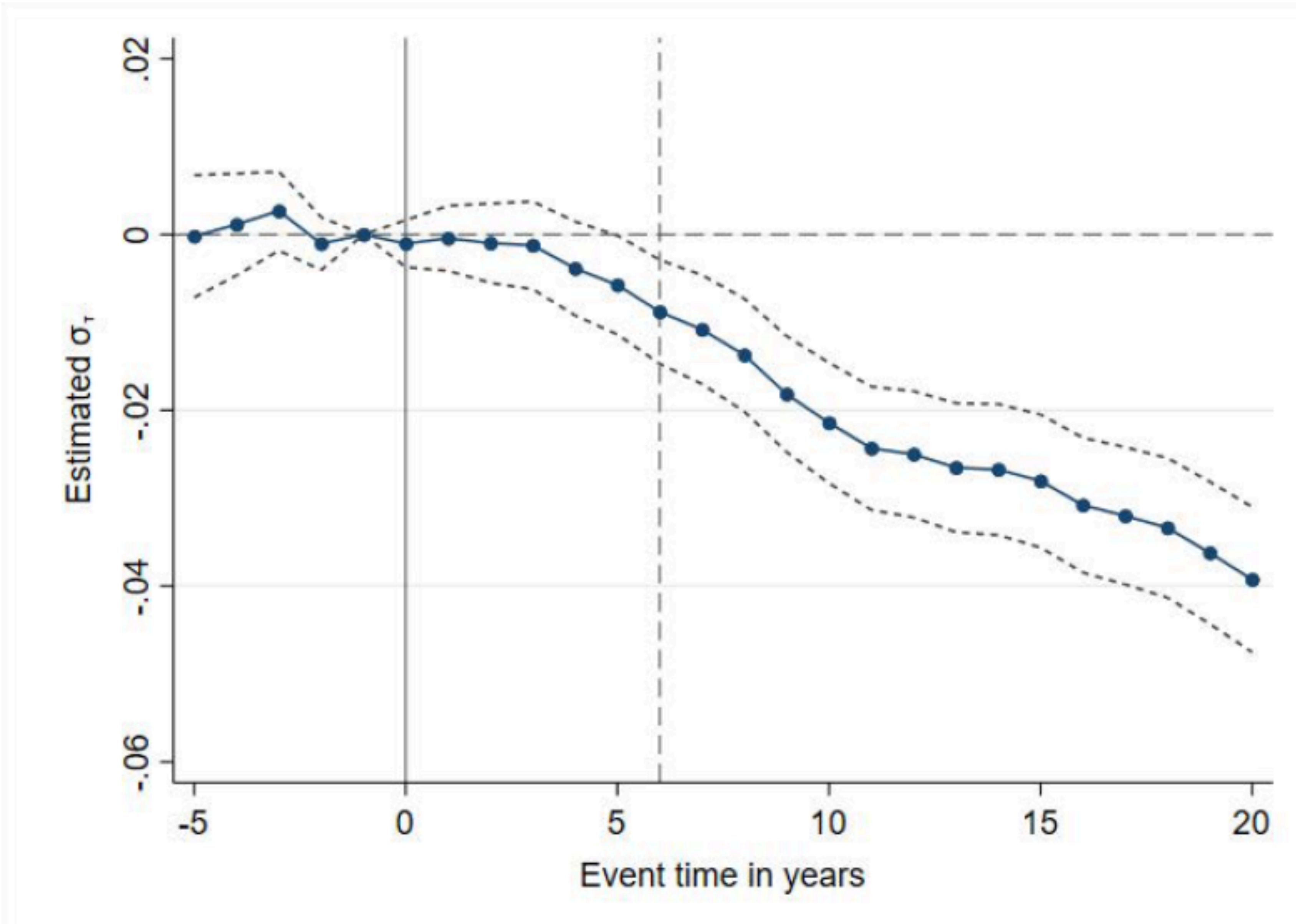
Figure 9: Doctor in the Family and Long-Run Health Bonus: Event Studies

A. Mortality



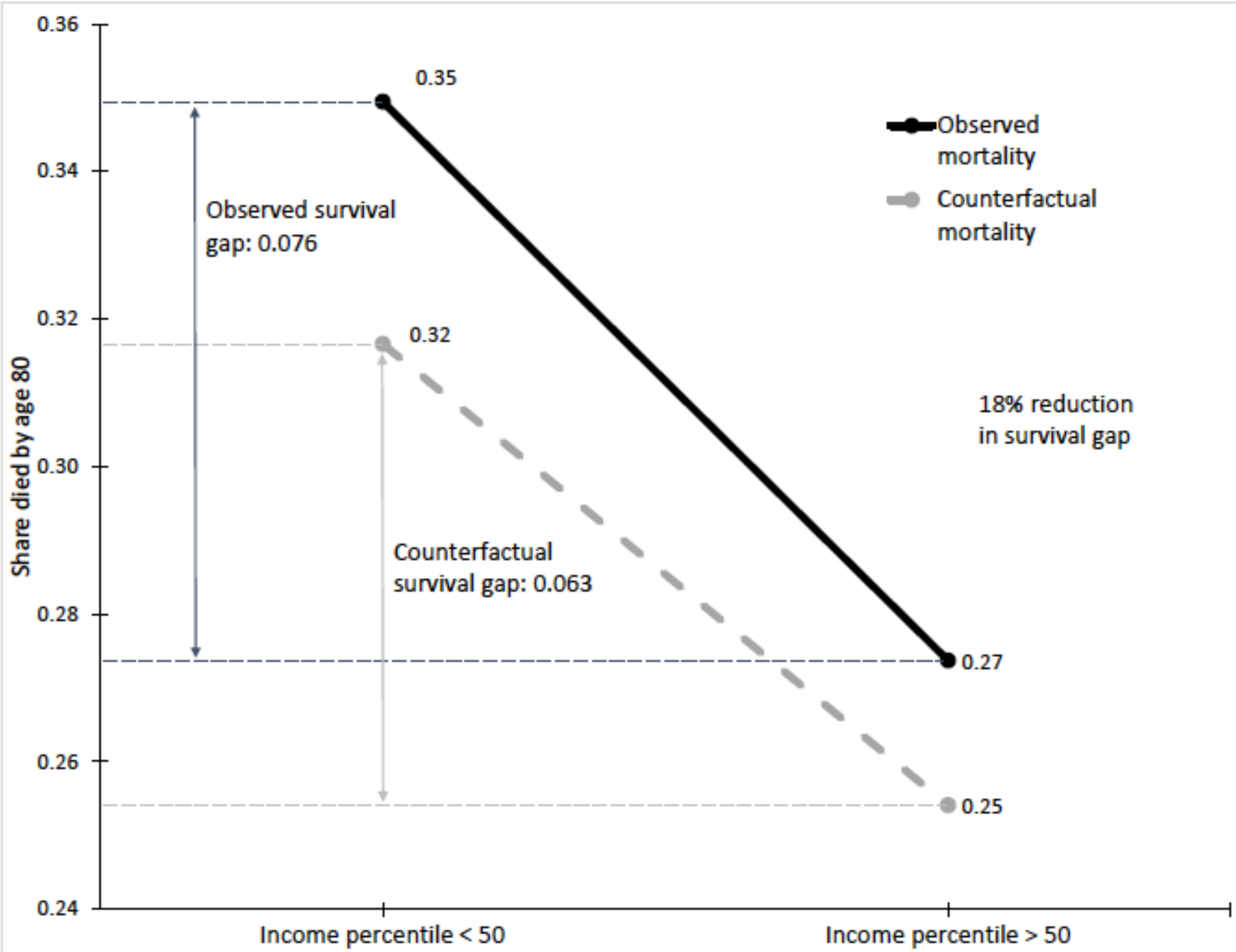
Having a Health Professional in the Family

B. Lifestyle-Related Conditions



Having a Health Professional in the Family

B. Universal access to expertise

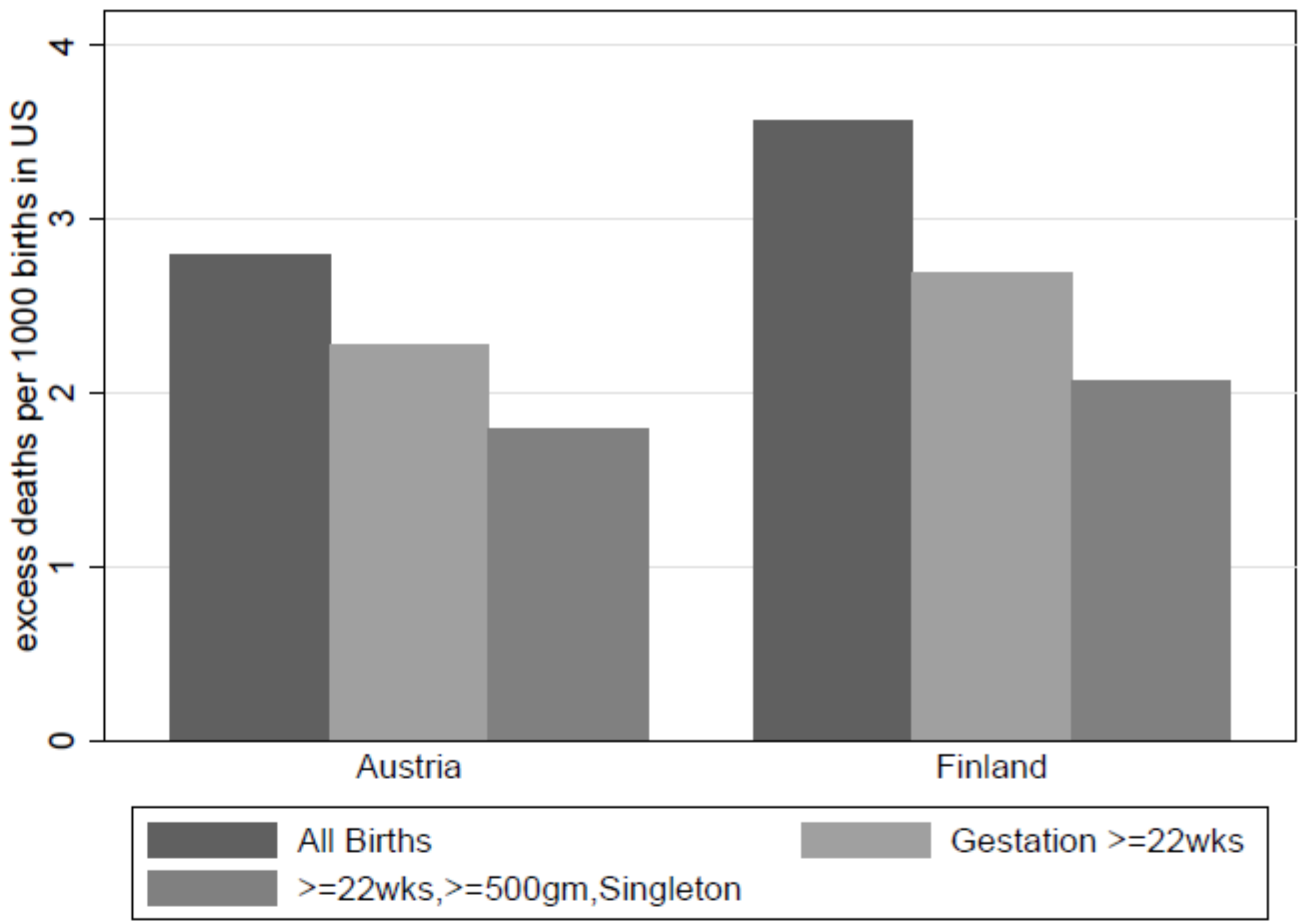


Outline

- Health Gradients
- Socioeconomic Disparities
- **Social Determinants of Health**

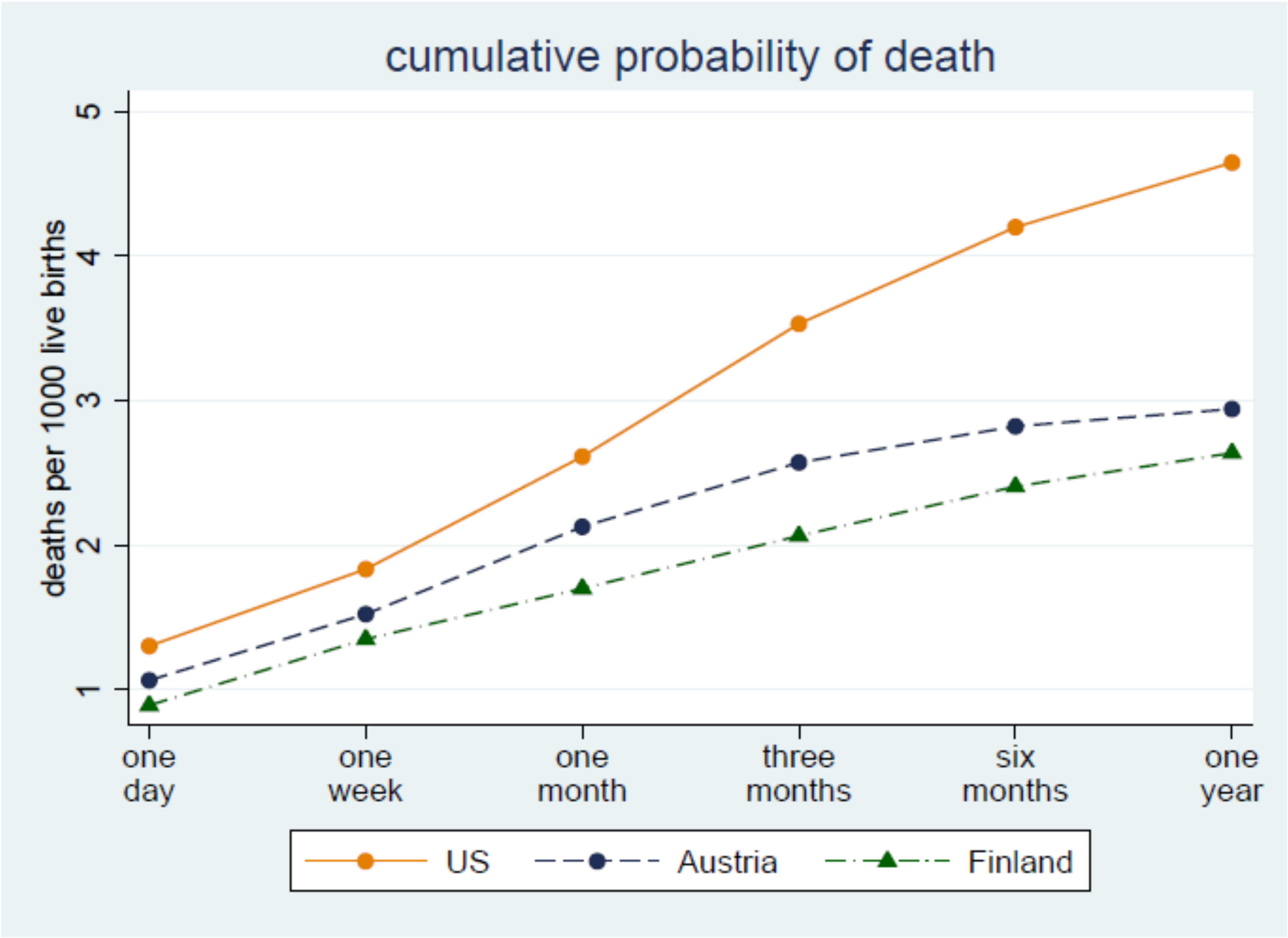
Infant mortality [Chen-Oster-Williams *AEJ-Policy*]

Figure 1: **US IMR disadvantage: Full sample and restricted samples**



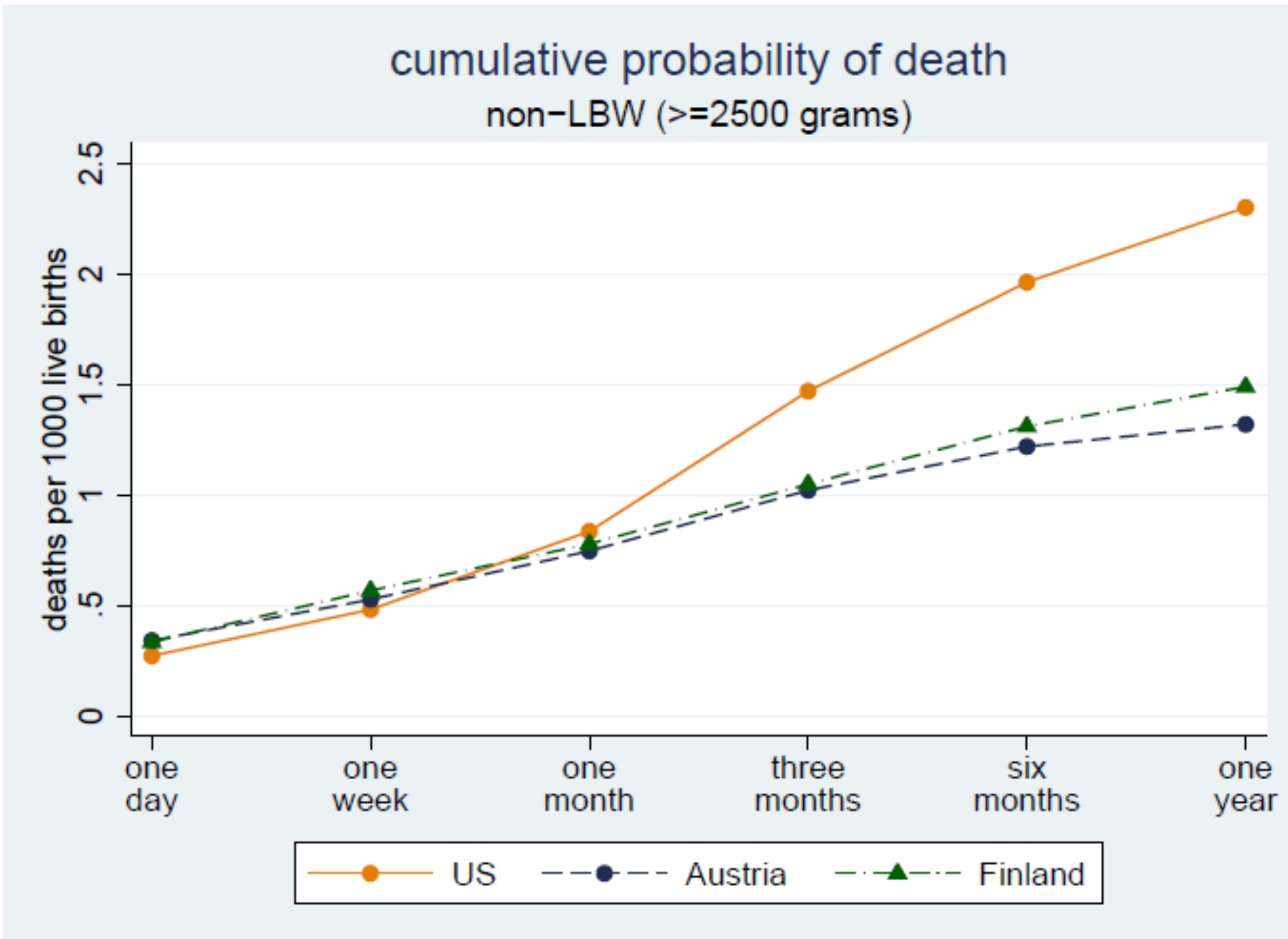
Infant mortality [Chen-Oster-Williams *AEJ-Policy*]

Figure 3: **Cumulative probability of death, by country**



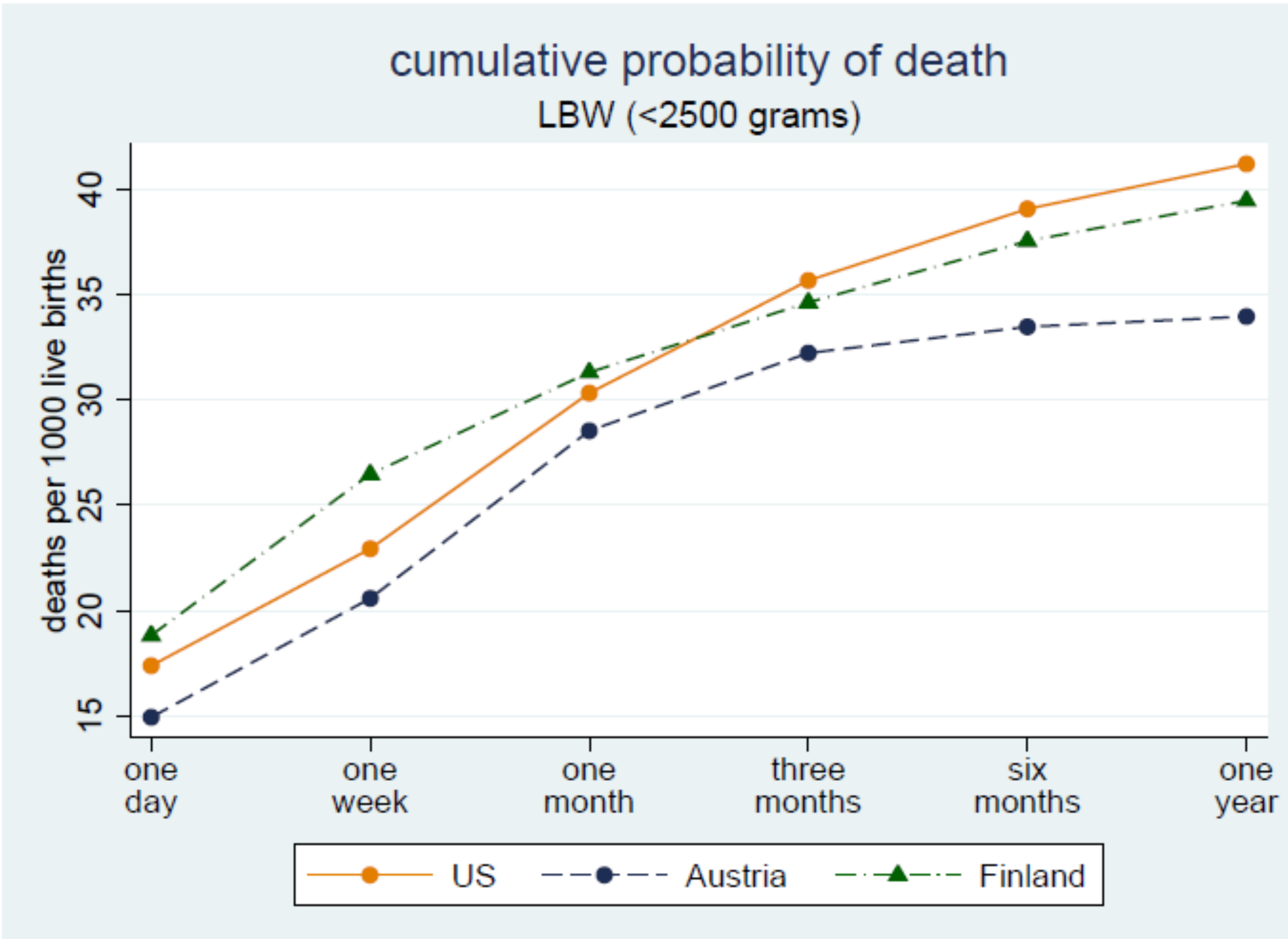
Infant mortality [Chen-Oster-Williams *AEJ-Policy*]

(a) Normal birth weight only (>=2500 grams)



Infant mortality [Chen-Oster-Williams *AEJ-Policy*]

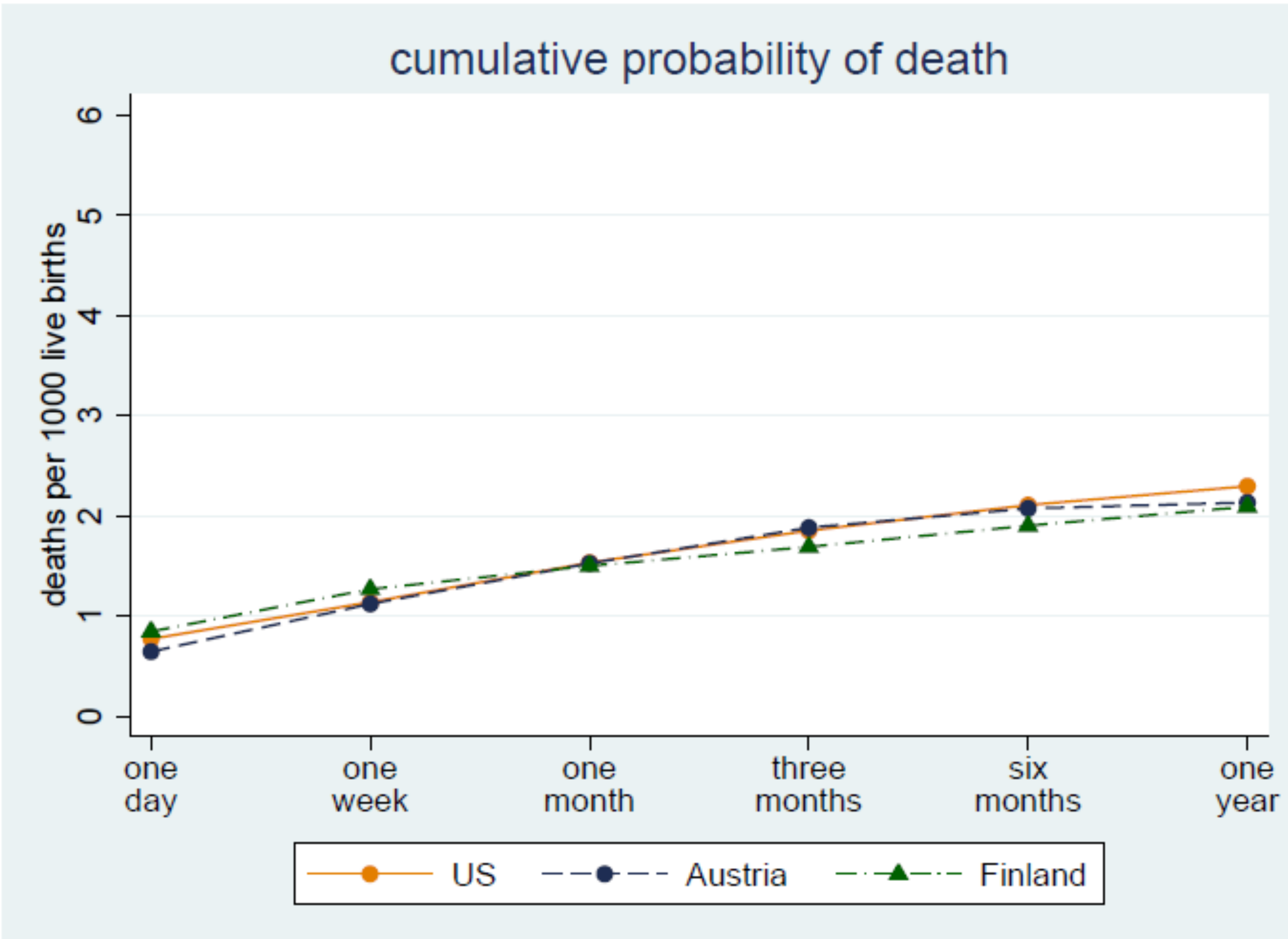
(b) Low birth weight only (<2500 grams)



Infant mortality [Chen-Oster-Williams *AEJ-Policy*]

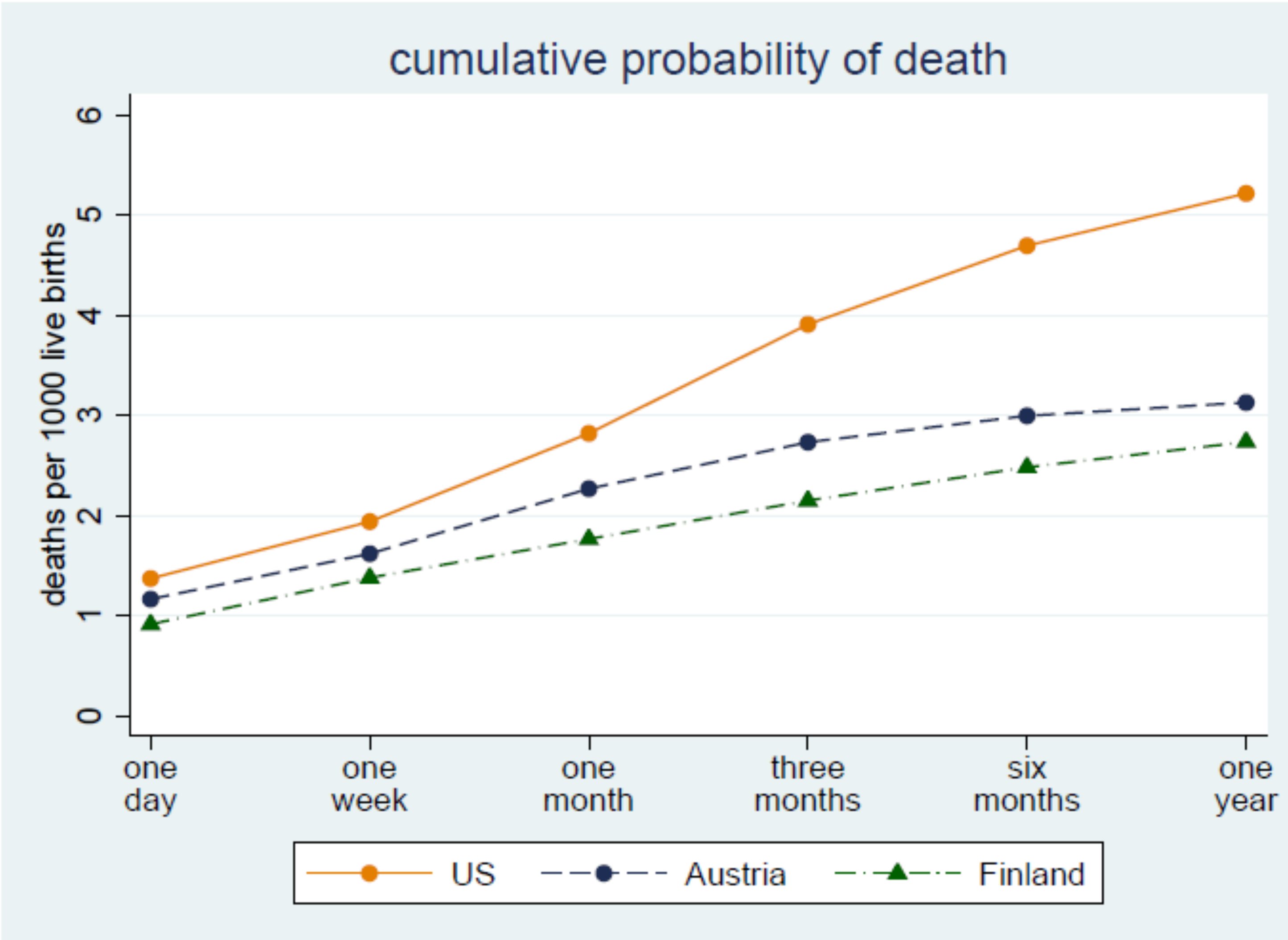
Figure 5: **Cumulative probability of death, by country, by group**

(a) Advantaged group



Infant mortality [Chen-Oster-Williams *AEJ-Policy*]

(b) Less advantaged group



Infant mortality

"[T]he US neonatal mortality disadvantage is quantitatively small and appears to be fully explained by differences in conditions at birth. By contrast, the US has a substantial disadvantage relative to Finland and Austria in the ***postneonatal period*** *even in our comparably reported sample and even conditional on circumstances at birth.*

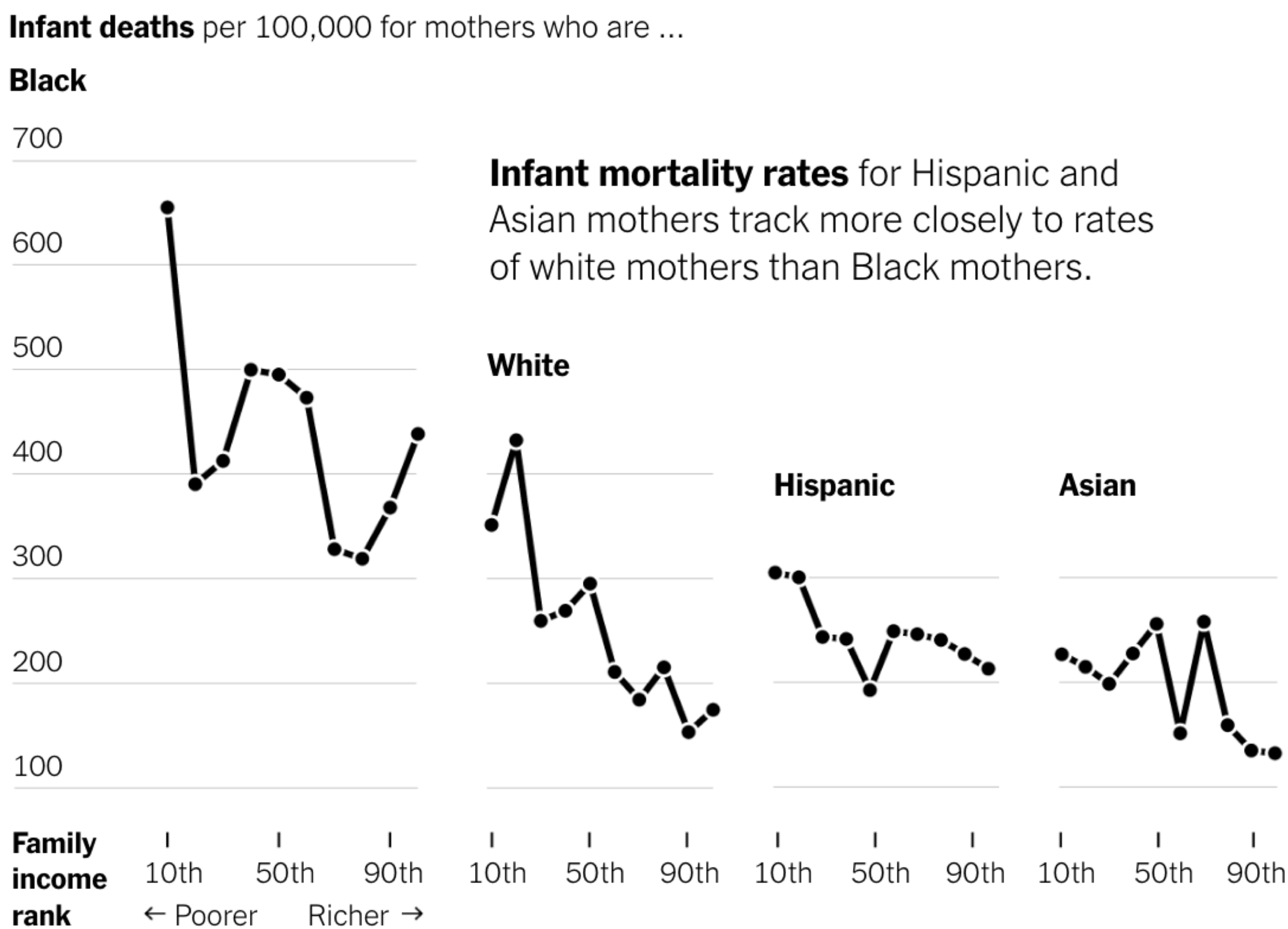
...

*"Importantly, this excess postneonatal mortality does not appear to be driven by the US delaying potential neonatal deaths**: the postneonatal disadvantage appears even among normal birth weight infants and those with high APGAR scores.***

...

"We document that the US postneonatal disadvantage is driven almost entirely by excess mortality among individuals of lower socioeconomic status. We show that infants born to white, college-educated, married women in the US have mortality rates that are essentially indistinguishable from a similar advantaged demographic in Austria and Finland."

Infant mortality (more recent evidence)



Source: https://www.nytimes.com/interactive/2023/02/12/upshot/child-maternal-mortality-rich-poor.html

Nurse-Family Partnership

Randomized Evaluation of the Nurse-Family Partnership

There is enormous policy interest in expanding programs that move beyond traditional health care walls into the community to improve health outcomes – and holding those programs financially responsible for doing so. Billions of public dollars are devoted to "home visiting" programs that seek to improve birth and long-term outcomes for low-income mothers and children. The Nurse-Family Partnership (NFP) program provides regular nurse home visits to low-income, first-time mothers through pregnancy and up to the first two years postpartum in order to improve the outcomes of both mothers and their children. South Carolina obtained a Medicaid waiver and generous philanthropic support to fund a landmark pay-for-success initiative that expanded NFP's services across the state. This randomized evaluation will assess a number of "success indicators" relevant to the pay-for-success initiative, such as the program's effectiveness in reducing injuries among newborns and toddlers, as well as study the potentially wide-ranging effects of NFP on the health and well-being of mothers and children for many years to come. The study aims to yield insights into the effectiveness of home visiting programs, the sustainability of more flexible public insurance benefits, and the potential role that evidence-based payments can play in driving improved outcomes.

Source: www.povertyactionlab.org/initiative-project/randomized-evaluation-nurse-family-partnership

Nurse-Family Partnership

The Impact of a Nurse Home Visiting Program on Maternal and Early Childhood Outcomes in the United States

Researchers: Margaret McConnell, Slawa Rokicki, Samuel Ayers, Farah Allouch, Nicolas Perreault, Rebecca A. Gourevitch, Michelle W. Martin, Annetta Zhou, Chloe Zera, Michele Hacker, Alyna Chien, Katherine Baicker, Mary Ann Bates

Fieldwork by: J-PAL North America

Location: South Carolina

Sample: 5,670 Medicaid-eligible pregnant people

Timeline: 2016

Initiative(s): US Health Care Delivery Initiative

Target group: Children under five; Mothers and pregnant women

Outcome of interest: Mortality; Sexual and reproductive health; Health outcomes; Maternal health; Long-term results

Intervention type: Early childhood development; Health care delivery

Source: https://www.povertyactionlab.org/evaluation/impact-nurse-home-visiting-program-maternal-and-early-childhood-outcomes-united-states

Nurse-Family Partnership: **RCT results**

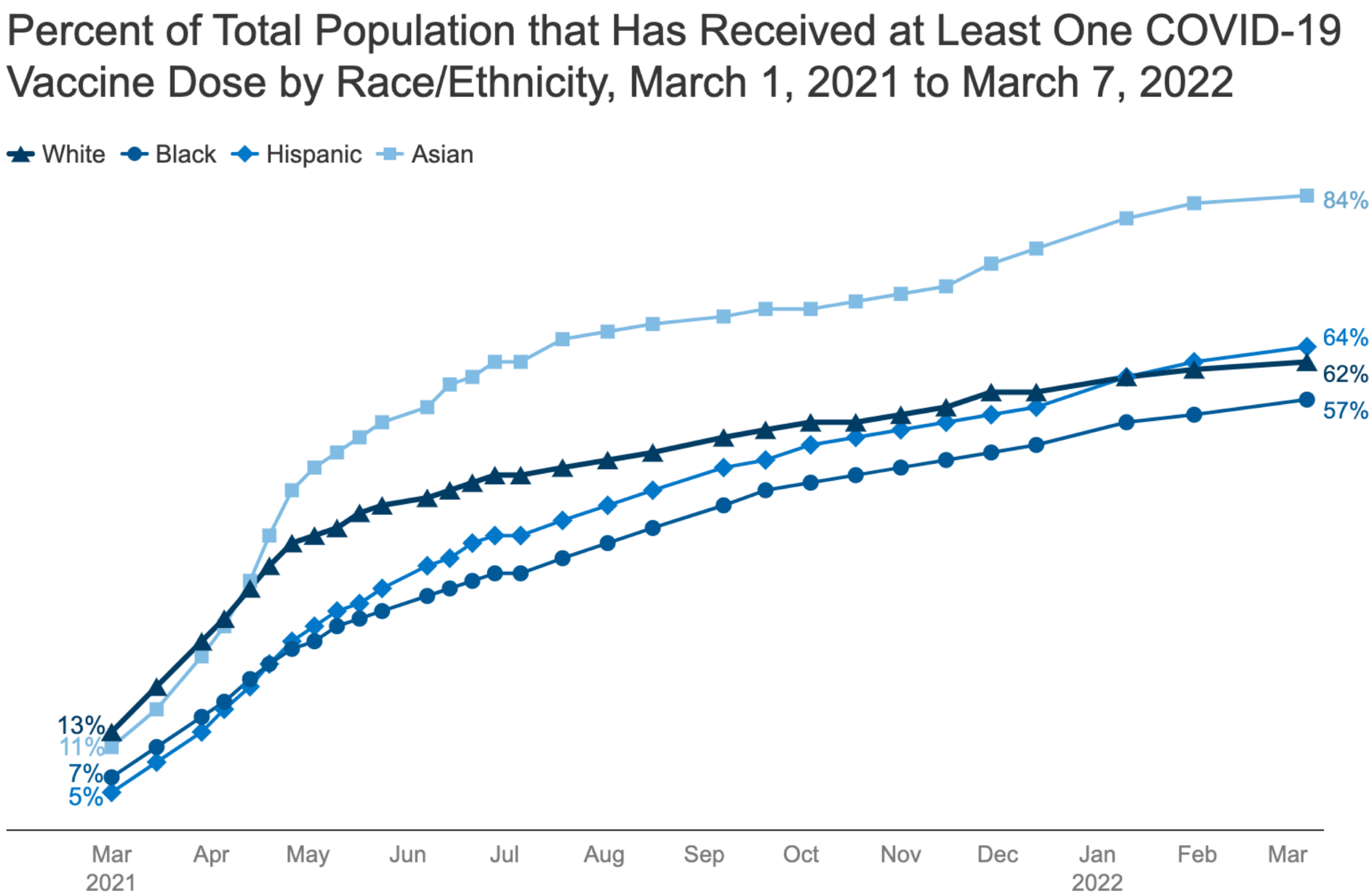
Adverse birth outcomes

There was no statistically significant effect of receiving NFP services on the primary composite outcome of adverse birth events, which included preterm birth, low birthweight, small-for-gestational-age birthweight, or perinatal mortality. 26.9 percent of participants who were randomized to receive NFP experienced an adverse birth outcome, compared to 26.1 percent of individuals who received usual care—a difference that was not statistically significant. There was also no detectable effect on any individual component of the composite, nor on nine other secondary outcomes (including the individual elements of the composite outcome, birthweight, gestational length, large-for-gestational-age, extremely preterm, very low birthweight, overnight NICU admission, severe maternal morbidity, and cesarean delivery). These results are consistent with other recent evaluations that have suggested home visiting does not reduce adverse birth outcomes.

The study did not find evidence of different effects for pre-specified subgroups of participants. Black individuals who received usual care experienced adverse birth events at a higher rate (31.6 percent) than the average for the usual care group overall (26.1 percent), but NFP services caused no statistically significant impacts on any adverse birth outcomes for Black individuals. There was also no difference between the intervention and usual care groups in any outcome for individuals identified as being particularly vulnerable to challenges during pregnancy and early childhood based on characteristics identified in prior home visiting trials (those who were younger than 19 years old, had not finished high school, or had challenges with mental health), who are prioritized by many current home visiting programs.

Source: https://www.povertyactionlab.org/evaluation/impact-nurse-home-visiting-program-maternal-and-early-childhood-outcomes-united-states

Medical mistrust



SOURCE: Vaccination data based on KFF analysis of publicly available data on state websites; total population data used to calculate rates based on KFF analysis of 2019 American Community Survey data. Number of states included in analysis varies based on available data at time of data collection. • PNG

Medical mistrust

- Today, medical mistrust is particularly heightened among Black men: “Black men exhibit higher levels of medical mistrust and this is correlated with reduced probabilities of routine, preventive, and early-stage disease care”

- Brandon et al. (2005) surveyed adults in 3 large US cities and found that a majority of Black respondents with knowledge of the **Tuskegee Study** believed that researchers had injected men with syphilis

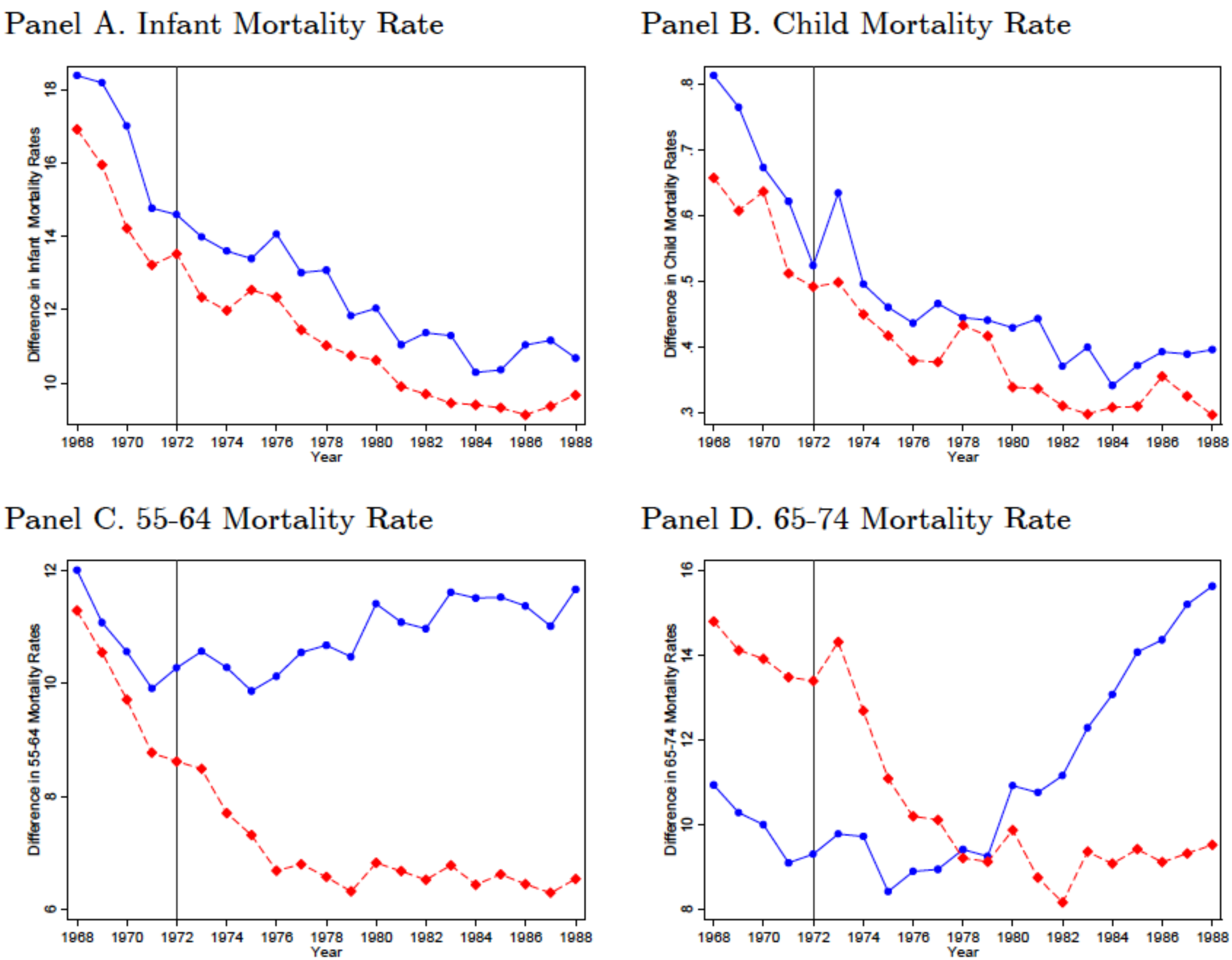
- Thomas and Quinn (1991): “The belief that AIDS is a form of genocide is rooted in a social context in which Black Americans … believe in conspiracy theories about Whites against Blacks. … An open and honest discussion of the Tuskegee Syphilis Study can facilitate the process of rebuilding trust between the Black community and public health authorities”

Tuskegee Study

- Designed to study the course of untreated syphilis in Black men in the US
- ~600 men recruited using incentives (free physical exams, hot meals, stipends paid to survivors) and were followed passively for ~40 years
- Public disclosure of study in 1972 “continues to cast a long shadow over the relationship between African-Americans and the biomedical professions”
- Alsan-Wannamaker QJE paper evaluates the hypothesis that the public disclosure of the Tuskegee Study affected health of Black men by creating long-lasting medical mistrust

Medical mistrust

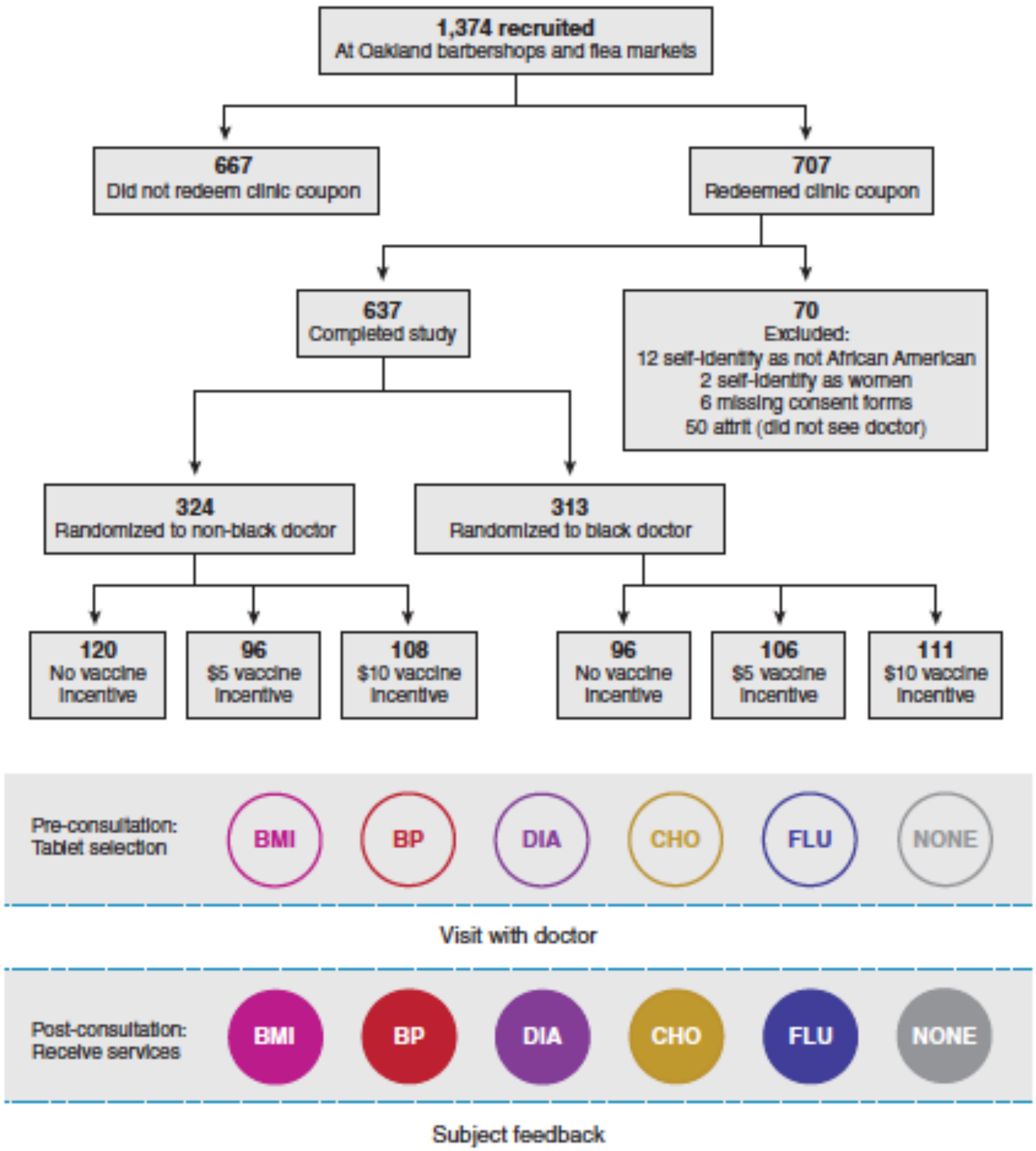
Figure I: Black-White Mortality Differences by Age and Sex



Tuskegee Study

Panel A. Distance to Tuskegee

Black medical doctors and preventive care



Black medical doctors and preventive care

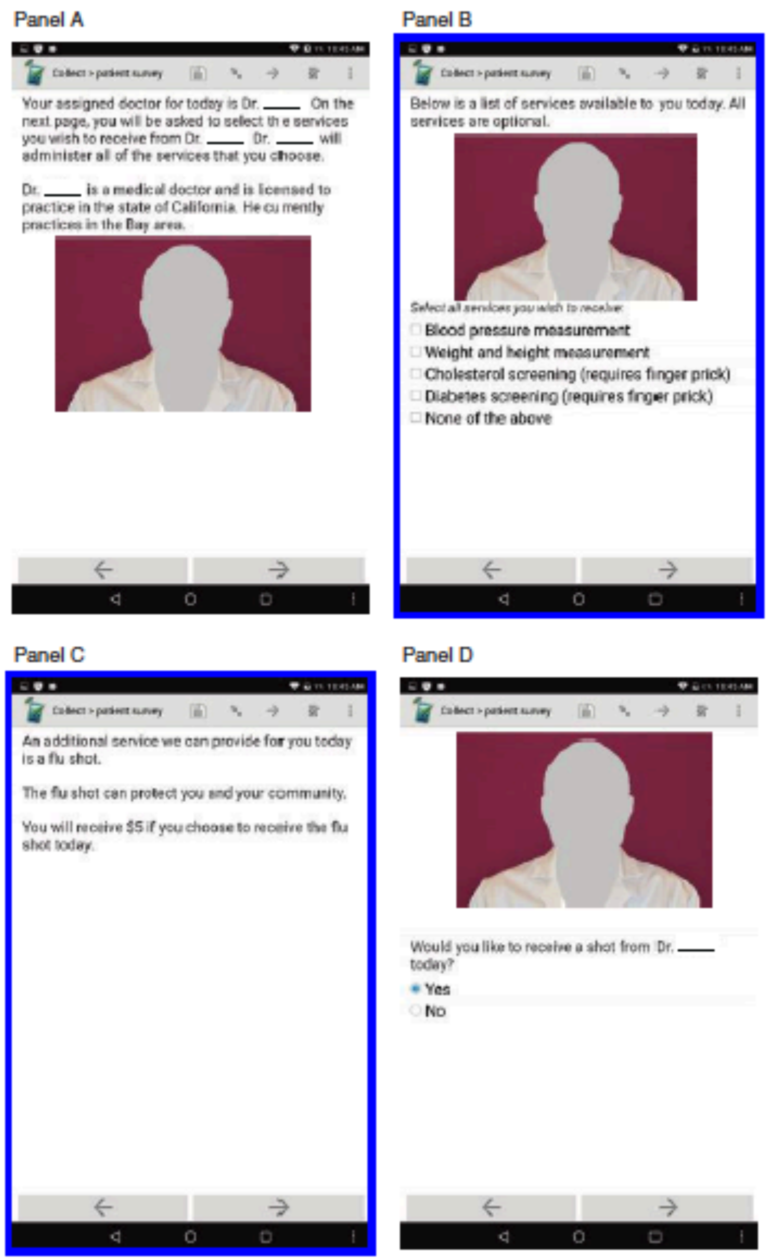
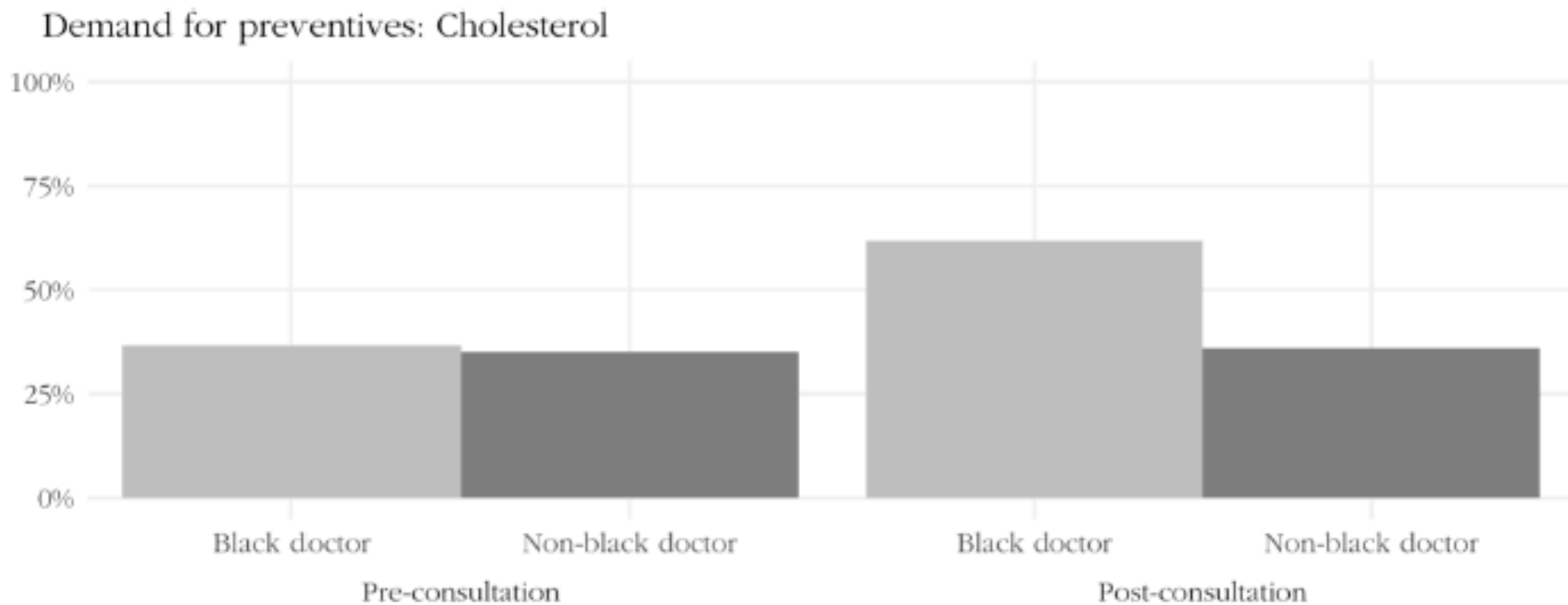


Figure 2. Tablet Photos

Black medical doctors and preventive care



This figure shows the share of Black men who choose to get screened for high cholesterol after consulting with a randomly assigned doctor. Before their consultation, only about one-third of the patients wanted a screening. After the consultation, if the Black men were randomly assigned a Black doctor, then they are more likely to choose a cholesterol screening compared to the Black men who were randomly assigned a Non-Black doctor.

Black medical doctors and preventive care

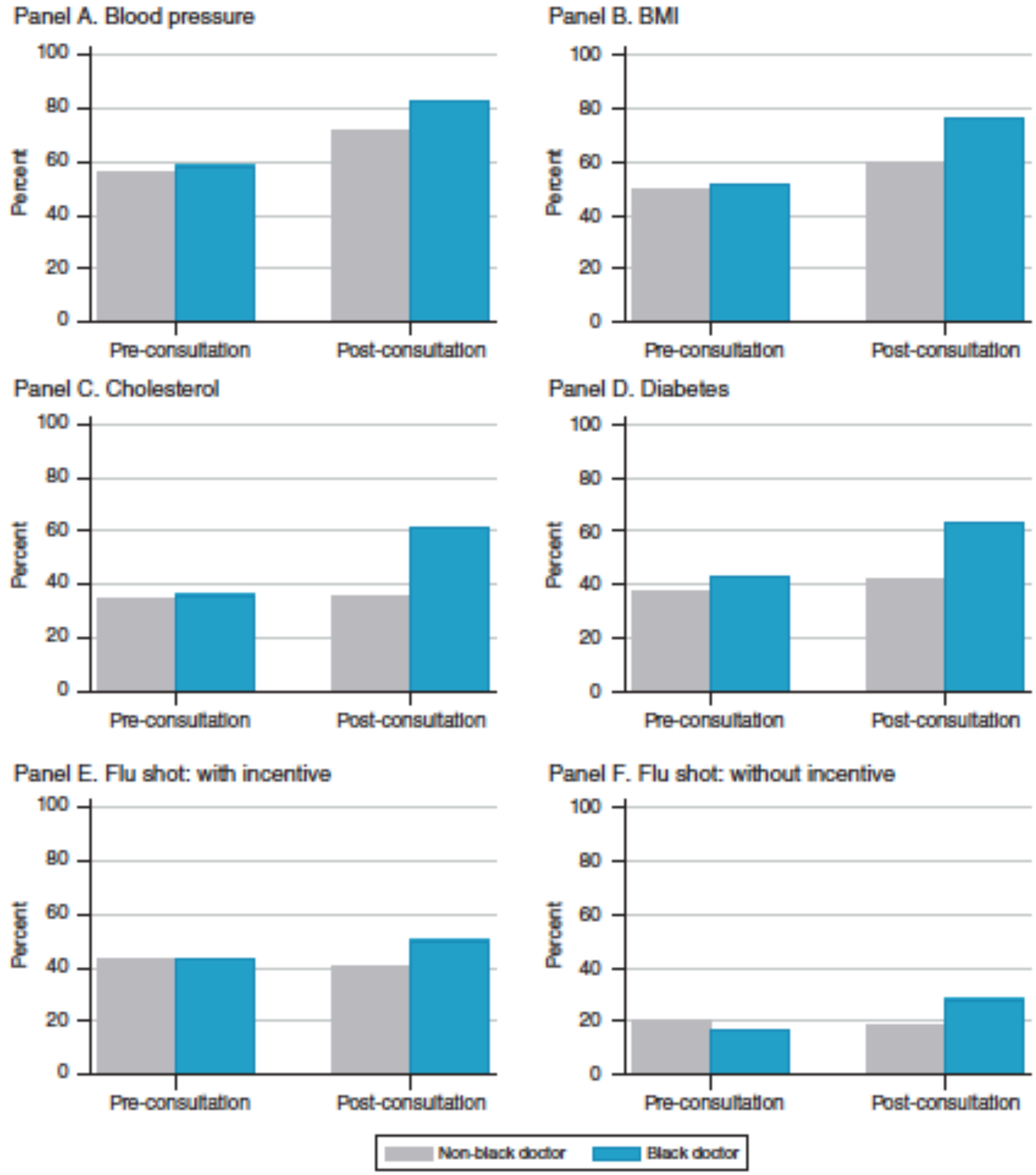
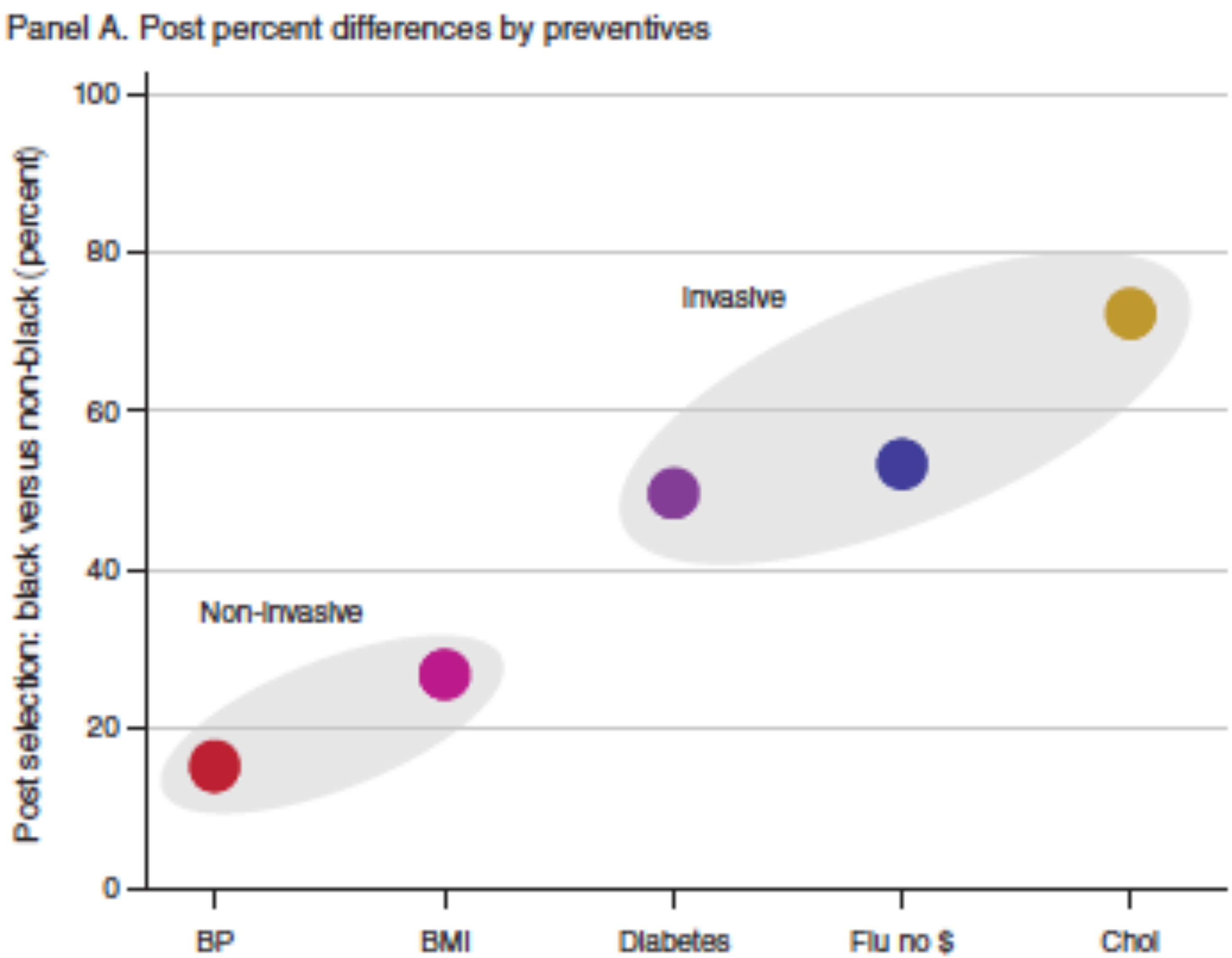
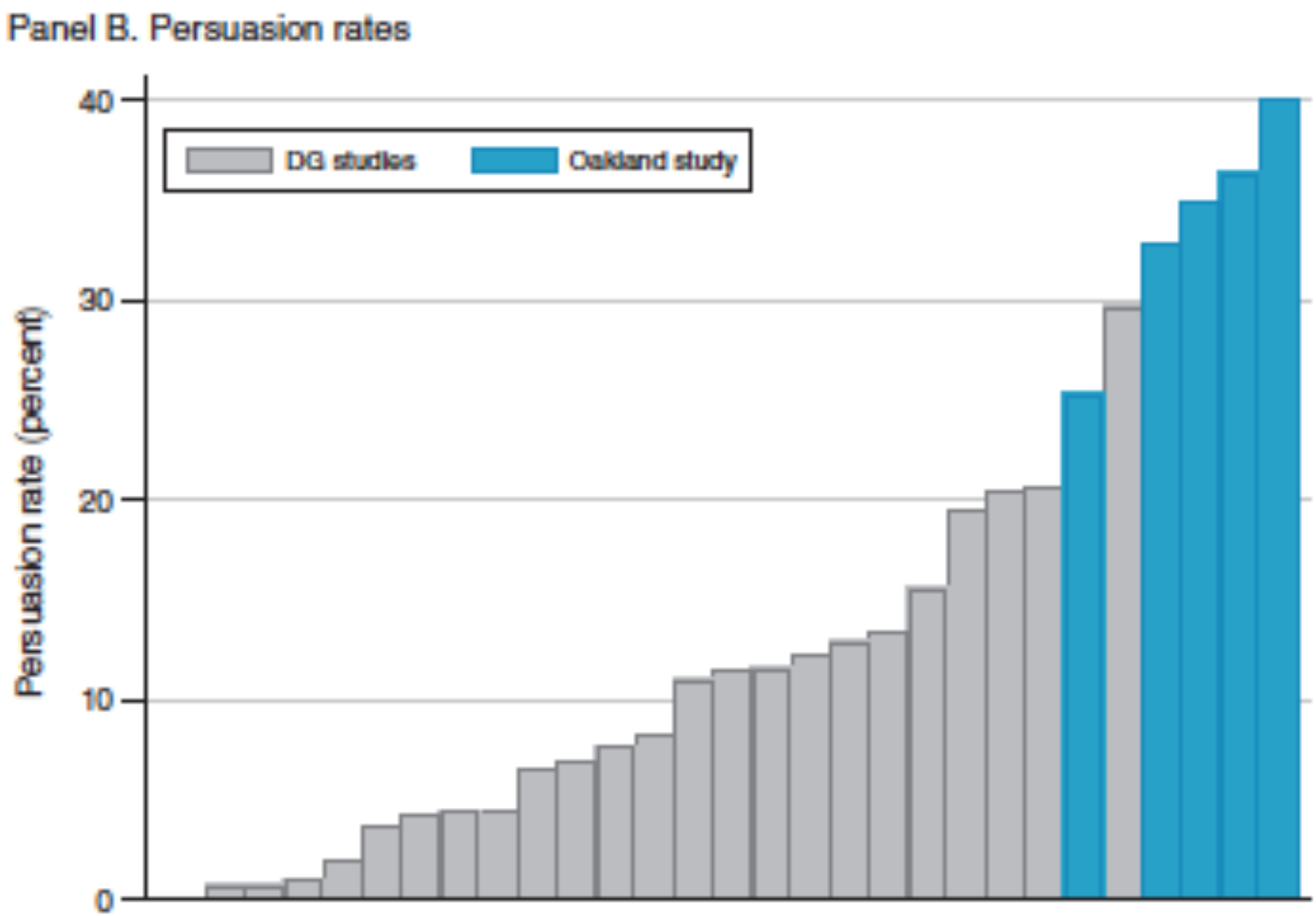


Figure 3. Demand for Preventives

Black medical doctors and preventive care



Black medical doctors and preventive care



MEDICAL REPORT

THE HOT SPOTTERS

By Atul Gawande

January 16, 2011

Could anything that dramatic happen here? An important idea is getting its test run in America: the creation of intensive outpatient care to target hot spots, and thereby reduce over-all health-care costs. But, if it works, hospitals will lose revenue and some will have to close. Medical companies and specialists profiting from the excess of scans and procedures will get squeezed. This will provoke retaliation, counter-campaigns, intense lobbying for Washington to obstruct reform.

MEDICAL REPORT

THE HOT SPOTTERS

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January 16, 2011

Critics say that it's a pipe dream—more money down the health-care sinkhole. They could turn out to be right, Brenner told me; a well-organized opposition could scuttle efforts like his. "In the next few years, we're going to have absolutely irrefutable evidence that there are ways to reduce health-care costs, and they are 'high touch' and they are at the level of care," he said. "We are going to know that, hands down, this is possible." From that point onward, he said, "it's a political problem." The struggle will be to survive the obstruction of lobbies, and the partisan tendency to view success as victory for the other side.

Hotspotting experiment

BACKGROUND

There is widespread interest in programs aiming to reduce spending and improve health care quality among "superutilizers," patients with very high use of health care services. The "hotspotting" program created by the Camden Coalition of Healthcare Providers (hereafter, the Coalition) has received national attention as a promising superutilizer intervention and has been expanded to cities around the country. In the months after hospital discharge, a team of nurses, social workers, and community health workers visits enrolled patients to coordinate outpatient care and link them with social services.

METHODS

We randomly assigned 800 hospitalized patients with medically and socially complex conditions, all with at least one additional hospitalization in the preceding 6 months, to the Coalition's care-transition program or to usual care. The primary outcome was hospital readmission within 180 days after discharge.

RESULTS

The 180-day readmission rate was 62.3% in the intervention group and 61.7% in the control group. The adjusted between-group difference was not significant (0.82 percentage points; 95% confidence interval, −5.97 to 7.61). In contrast, a comparison of the intervention-group admissions during the 6 months before and after enrollment misleadingly suggested a 38-percentage-point decline in admissions related to the intervention because the comparison did not account for the similar decline in the control group.

Hotspotting experiment

Table 1. Characteristics of the Patients at Baseline.*

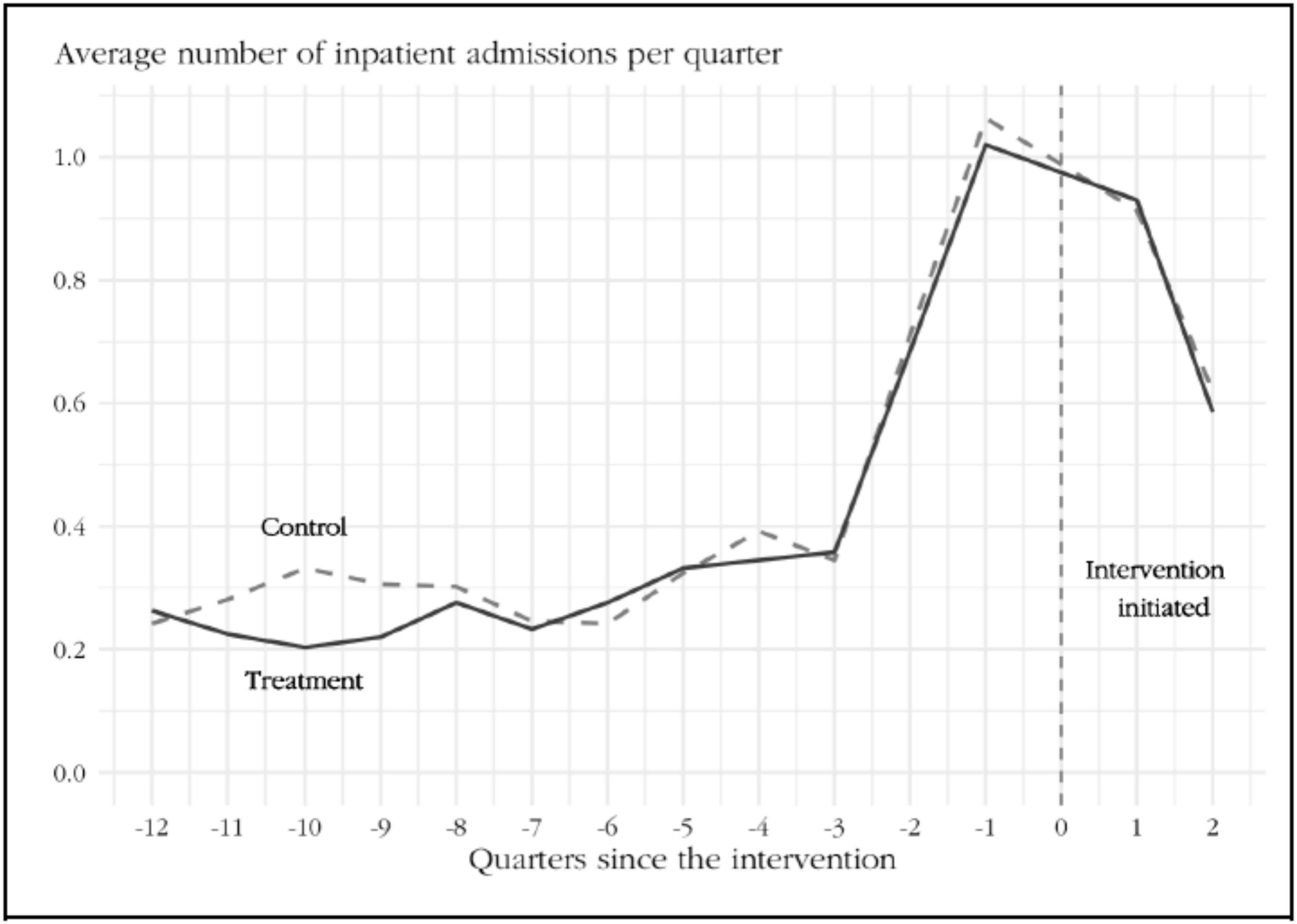
Characteristic	Overall (N=782)	Treatment (N=393)	Control (N=389)
Age at index admission (%)			
≤44 yr	17.1	16.0	18.3
45–64 yr	55.4	55.0	55.8
≥65 yr	27.5	29.0	26.0
Race or ethnic group (%)			
Non-Hispanic black	54.9	57.8	51.9
Hispanic	29.5	26.7	32.4
Non-Hispanic white	15.1	14.8	15.4
Asian, multiracial, or other	0.5	0.8	0.3
Inpatient admissions before index admission (no.)			
0–6 mo before	1.75	1.72	1.78
7–12 mo before	0.74	0.74	0.75
Primary payer (%)			
Medicaid	44.6	43.0	46.3
Medicare	48.2	47.6	48.8
Other	7.0	9.2	4.9
Employment status (%)			
Currently employed	5.5	4.8	6.2
Not employed	94.0	94.9	93.1
No response	0.5	0.3	0.8
Mental health diagnoses at index admission (%)			
Depression	30.2	32.3	28.0
Substance abuse	44.0	41.2	46.8

Hotspotting experiment

Table 4. Effects of Intervention in the Treatment Group, 180 Days after Discharge.*

Effect	No. of Patients	Control Group	Treatment Group	Unadjusted Between-Group Difference (95% CI)	Adjusted Between-Group Difference (95% CI)
		mean			
Readmission in total sample					
Any (%)		61.70	62.34	0.64 (−6.17 to 7.46)	0.82 (−5.97 to 7.61)
No. of readmissions		1.54	1.52	−0.02 (−0.29 to 0.26)	0.01 (−0.25 to 0.27)
≥2 readmissions (%)		36.25	36.39	0.14 (−6.61 to 6.89)	0.27 (−6.22 to 6.77)
Days in hospital		9.95	9.36	−0.59 (−2.49 to 1.31)	−0.32 (−2.17 to 1.53)
Hospital charges ($)		114,768	116,422	1,654 (−25,523 to 28,831)	3,722 (−23,438 to 30,882)
Hospital payments received ($)		17,650	18,130	480 (−3,613 to 4,573)	680 (−3,415 to 4,775)
Any readmission according to subgroup (%)					
No. of admissions in previous yr					
2	336	52.12	52.63	0.51 (−10.2 to 11.22)	0.78 (−10.35 to 11.91)
≥3	446	68.75	69.82	1.07 (−7.51 to 9.65)	1.27 (−7.38 to 9.92)
Preferred language					
English	638	63.11	62.61	−0.49 (−8.01 to 7.02)	0.1 (−7.42 to 7.61)
Other	144	56.25	60.94	4.69 (−11.58 to 20.96)	8.49 (−9.08 to 26.06)

Hotspotting experiment



Food-as-Medicine Program

Food Is Medicine: A Project to Unify and Advance Collective Action

Overview

The White House Conference on Hunger, Nutrition, and Health — held in September 2022 — renewed national attention and issued a call to action to end hunger and reduce the prevalence of chronic disease in the United States by 2030.

Food Is Medicine approaches that focus on integrating consistent access to diet- and nutrition- related resources are a critical component to achieve this goal. The approaches are increasingly present across many communities and systems. There's also increasing federal investment and action to support Food Is Medicine approaches in a variety of settings.

Source: https://health.gov/our-work/nutrition-physical-activity/food-medicine

Food-as-Medicine Program

JAMA Intern Med. 2023 Dec 26:e236670. doi: 10.1001/jamainternmed.2023.6670.
Online ahead of print.

Effect of an Intensive Food-as-Medicine Program on Health and Health Care Use: A Randomized Clinical Trial

Joseph Doyle [1], Marcella Alsan [2], Nicholas Skelley [3], Yutong Lu [3], John Cawley [4]

Source: https://health.gov/our-work/nutrition-physical-activity/food-medicine

Food-as-Medicine Program

Abstract

Importance: Food-as-medicine programs are becoming increasingly common, and rigorous evidence is needed regarding their effects on health.

Objective: To test whether an intensive food-as-medicine program for patients with diabetes and food insecurity improves glycemic control and affects health care use.

Design, setting, and participants: This stratified randomized clinical trial using a wait list design was conducted from April 19, 2019, to September 16, 2022, with patients followed up for 1 year. Patients were randomly assigned to either participate in the program immediately (treatment group) or 6 months later (control group). The trial took place at 2 sites, 1 rural and 1 urban, of a large, integrated health system in the mid-Atlantic region of the US. Eligibility required a diagnosis of type 2 diabetes, a hemoglobin A1c (HbA1c) level of 8% or higher, food insecurity, and residence within the service area of the participating clinics.

Intervention: The comprehensive program provided healthy groceries for 10 meals per week for an entire household, plus dietitian consultations, nurse evaluations, health coaching, and diabetes education. The program duration was typically 1 year.

Main outcomes and measures: The primary outcome was HbA1c level at 6 months. Secondary outcomes included other biometric measures, health care use, and self-reported diet and healthy behaviors, at both 6 months and 12 months.

Source: https://health.gov/our-work/nutrition-physical-activity/food-medicine

Food-as-Medicine Program

Results: Of 3712 patients assessed for eligibility, 3168 were contacted, 1064 were deemed eligible, 500 consented to participate and were randomized, and 465 (mean [SD] age, 54.6 [11.8] years; 255 [54.8%] female) completed the study. Of those patients, 349 (mean [SD] age, 55.4 [11.2] years; 187 [53.6%] female) had laboratory test results at 6 months after enrollment. Both the treatment (n = 170) and control (n = 179) groups experienced a substantial decline in HbA1c levels at 6 months, resulting in a nonsignificant, between-group adjusted mean difference in HbA1c levels of -0.10 (95% CI, -0.46 to 0.25; P = .57). Access to the program increased preventive health care, including more mean (SD) dietitian visits (2.7 [1.8] vs 0.6 [1.3] visits in the treatment and control groups, respectively), patients with active prescription drug orders for metformin (134 [58.26] vs 119 [50.64]) and glucagon-like peptide 1 medications (114 [49.56] vs 83 [35.32]), and participants reporting an improved diet from 1 year earlier (153 of 164 [93.3%] vs 132 of 171 [77.2%]).

Conclusion: *"Programs targeted to individuals with elevated biomarkers require a control group to demonstrate effectiveness to account for improvements that occur without the intervention. Additional research is needed to design food-as-medicine programs that improve health."*

Source: https://health.gov/our-work/nutrition-physical-activity/food-medicine

Conclusions

- Large health disparities and health "gradients" in the US and many other countries, and I think the evidence points against the gradients arising primarily from the causal effect of wealth or income on health
- Growing amount of work on "Social Determinants of Health", but many promising programs (NFP, hotspotting, food-as-medicine) have not looked as promising after being subjected to rigorous RCTs – more research and more experiments are needed!
- The "gradients" by race, education, and income matter for social welfare. Paraphrasing Lucas, *"once you start thinking about mortality, it's hard to think about anything else"*

Bonus slides

Mortality and Welfare

Beyond GDP? Welfare across Countries and Time

Charles I. Jones

Peter J. Klenow

AMERICAN ECONOMIC REVIEW
VOL. 106, NO. 9, SEPTEMBER 2016
(pp. 2426-57)

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We propose a summary statistic for the economic well-being of people in a country. Our measure incorporates consumption, leisure, mortality, and inequality, first for a narrow set of countries using detailed micro data, and then more broadly using multi-country datasets. While welfare is highly correlated with GDP per capita, deviations are often large. Western Europe looks considerably closer to the United States, emerging Asia has not caught up as much, and many developing countries are further behind. Each component we introduce plays a significant role in accounting for these differences, with mortality being most important.

Mortality and Welfare

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Mortality and Welfare

Model Setup: Utility

- Large N of ex-ante identical agents
- **Expected lifetime utility:**

$$U(c(t), m(t)) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t S(m(t)) u(c(t)) \right]$$

  - $m(t)$ is the mortality rate (indexed by t to allow it to vary over life cycle)
  - $S(m(t))$ is cumulative survival function
  - β is the agent's discount rate
- **Per-period utility function**:

$$u(c) = b + \frac{c^{1-\gamma}}{1-\gamma}$$

  - γ governs how quickly MU of consumption declines with consumption
  - b determines WTP for additional year of life (VSLY) [VSLY]

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Mortality and Welfare

VSLY Formula

- The Value of a Statistical Life Year (VSLY) is given by:

$$\text{VSLY} = \frac{U(c,m)/u'(c)}{T} = bc^{\gamma} - \frac{c}{\gamma - 1}$$

- VSLY is thus increasing in c for $\gamma > 1$

Almond, Chay, Greenstone – The Civil Rights Act and Black-White Convergence in IMR

In 1965, 40 African American infants died for every 1,000 born in the U.S. – a rate comparable to current levels in India or Iran. Over the next ten years, the infant mortality rate among U.S. blacks fell to 24 per thousand. Among black infants born in 1975, roughly 7,000 more babies survived to age 1 than if the pre-1965 trend had continued. Further, the gap between black and white infant mortality rates (IMR) narrowed substantially during the late 1960s and early 1970s (Figure 1a). Indeed, these years comprise the sole period of large reductions in the black-white infant mortality gap since World War II

Almond, Chay, Greenstone – The Civil Rights Act and Black-White Convergence in IMR

- Hospital payments under Medicare were conditioned on elimination of "whites-only" hospitals. Financial leverage led to large increases in access to care for blacks.

- Most compelling results in paper come from detailed case study on Mississippi, where hospitals were slow to integrate despite the financial incentive to do so. Leads to sharp "event study" analysis.

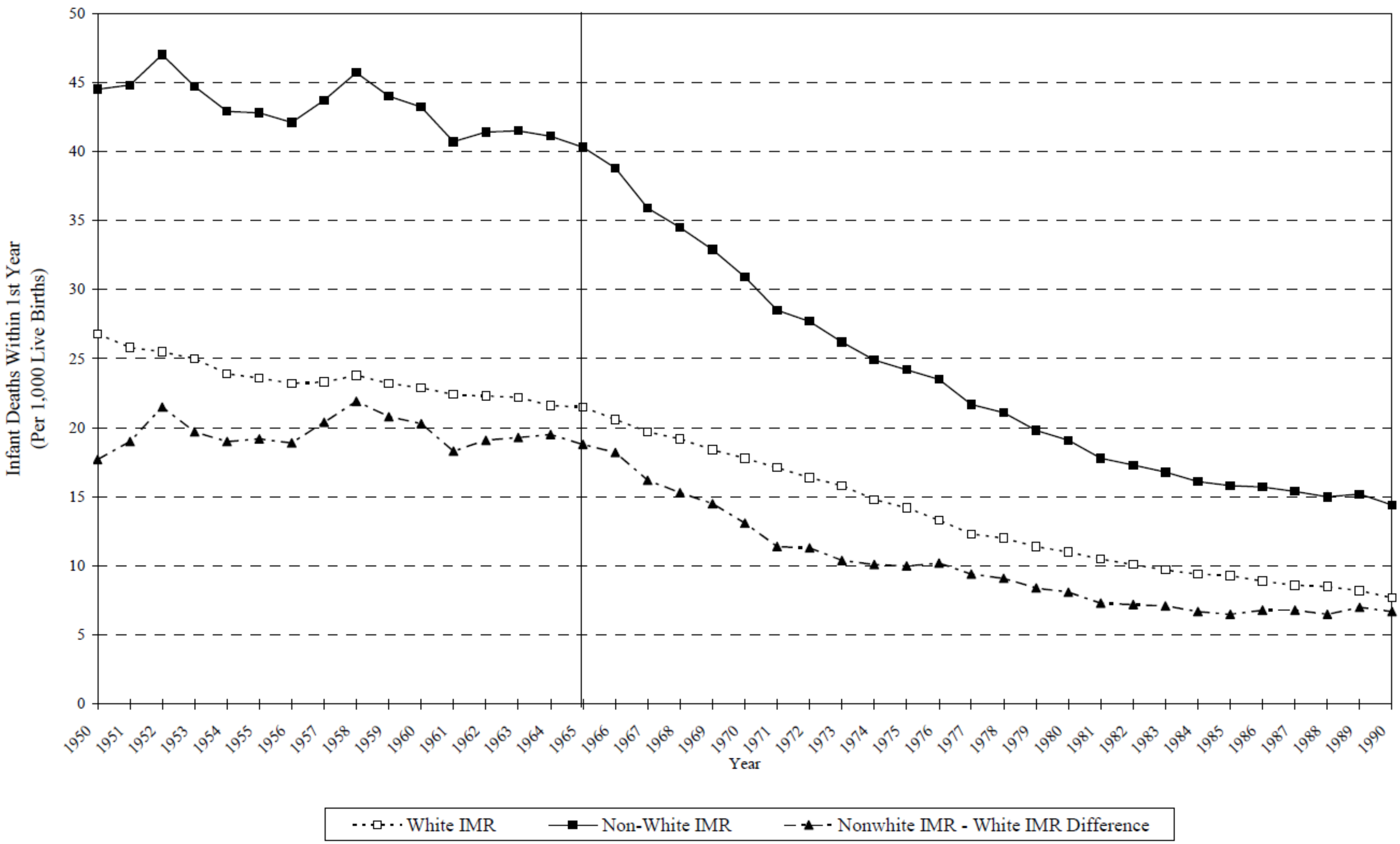
Almond, Chay, Greenstone – The Civil Rights Act and Black-White Convergence in IMR

Table 1: Black Access to Hospital Care Before Title VI of 1964 Civil Rights Act

	(1)	(2)	(3)
A. Fraction of Births Occurring in a Hospital with Physician Present, 1955-1965			
	Black	White	Black-white Difference
Urban Rustbelt	97.0	99.3	2.4
Urban Elsewhere	98.4	99.4	1.0
Urban South	92.8	98.4	5.6
Rural South	60.1	95.9	35.7
Mississippi	47.6	98.1	50.5

Almond, Chay, Greenstone – The Civil Rights Act and Black-White Convergence in IMR

Figure 1a: Trends in the Infant Mortality Rate by Race, 1950-1990



Almond, Chay, Greenstone – The Civil Rights Act and Black-White Convergence in IMR

Figure 1b: Number of Post-Neonatal Infant Deaths due to Diarrhea and Pneumonia by Race in Mississippi, 1955-1975