Topic 10: Welfare Analysis of Public Health Insurance

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[1] Thanks to Raj Chetty and Amy Finkelstein for generously providing their lecture notes, some of which are reproduced here

Public Health Insurance

- Medicaid is the largest transfer program in the US ($550B in 2015)
- Potential rationales for gov't provision:
  - Adverse selection
  - Samaritan's dilemma (uncompensated care)
  - Externalities on others
  - Productive impacts on children

Goals of This Lecture

- Impact of Public Health Insurance on Adults
  - Consumption smoothing / reducing high out of pocket spending
  - Increases in healthcare utilization (i.e. "moral hazard")
  - Labor supply
- Conduct/discuss welfare analysis
  - Structural assumptions vs. revealed preference
  - Role of uncompensated care
- Impact of health on Children
  - Large evidence of health impacts
- GE Effects
  - Insurance increases hospital expansion/innovation/etc
  - Leads to increased costs...

Key Themes: It's all about the kids...

- Insurance limits out of pocket payments and decreases financial stress
- Does not have (measurable) health impacts on adults
  - Large crowd-out of uncompensated care in recent expansions
  - The uninsured aren't fully "uninsured"
- Yet, Miller et al (2019) suggests positive health effects on adults
- Lots of evidence suggesting insurance improves health for children
  - Similar to MTO / neighborhoods?
- Strong evidence insurance increases costs through GE effects

1. Impact of Medicaid on Adults
2. Welfare Analysis of Medicaid
3. Impact Medicaid on Children
4. Impact of Medicare: Health and GE Effects

Oregon Health Insurance Experiment

- In 2008, Oregon ran a lottery for its Medicaid program for low-income adults
  - Was previously closed to new enrollment
  - Approximately 90,000 people signed up.
    - Budget for 10,000 people
  - Lotteried 30,000 with ~30% takeup
- Finkelstein et al. (2012, QJE "The Oregon Health Insurance Experiment: Evidence from the First Year")

Oregon Health Insurance Experiment

- Intention to treat specification

$$y_i = \beta_0 + \beta_1 LOTTERY_i + \beta_2 X_i + \epsilon_i$$

where X_i are covariates correlated with probability of winning the lottery (e.g. household size)

- LATE specification

$$y_i = \pi_0 + \pi_1 INSURANCE_i + \pi_2 X_i + \nu_i$$

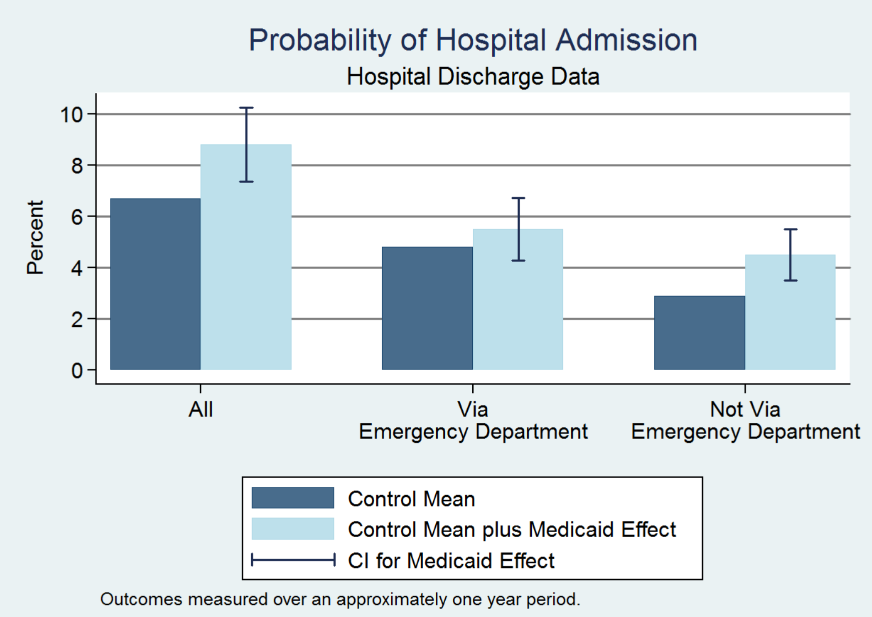
where first stage is

$$INSURANCE_i = \gamma_0 + \gamma_1 LOTTERY_i + \gamma_2 X_i + \eta_i$$

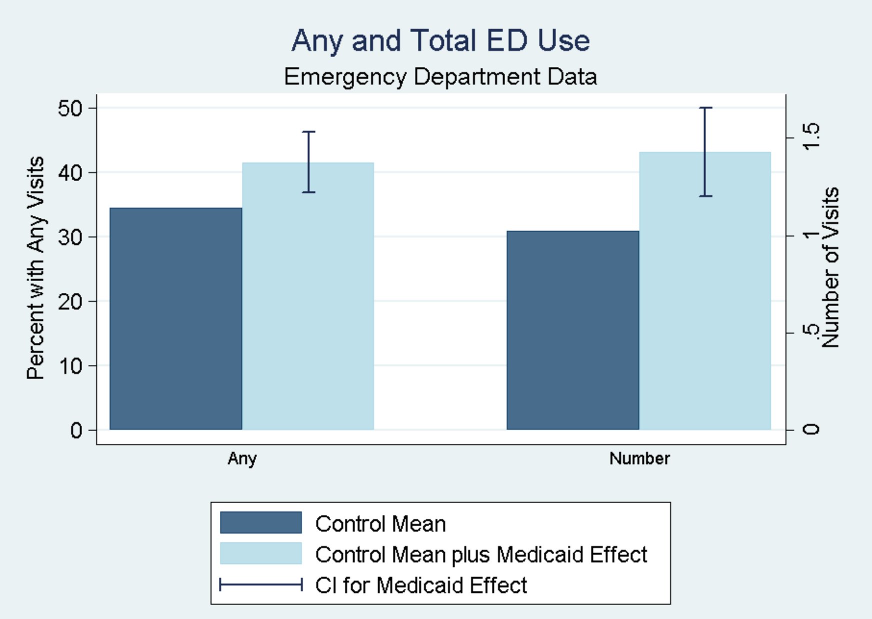
  - Compliers are those induced to get insurance through the lottery

- Begin with impacts on utilization

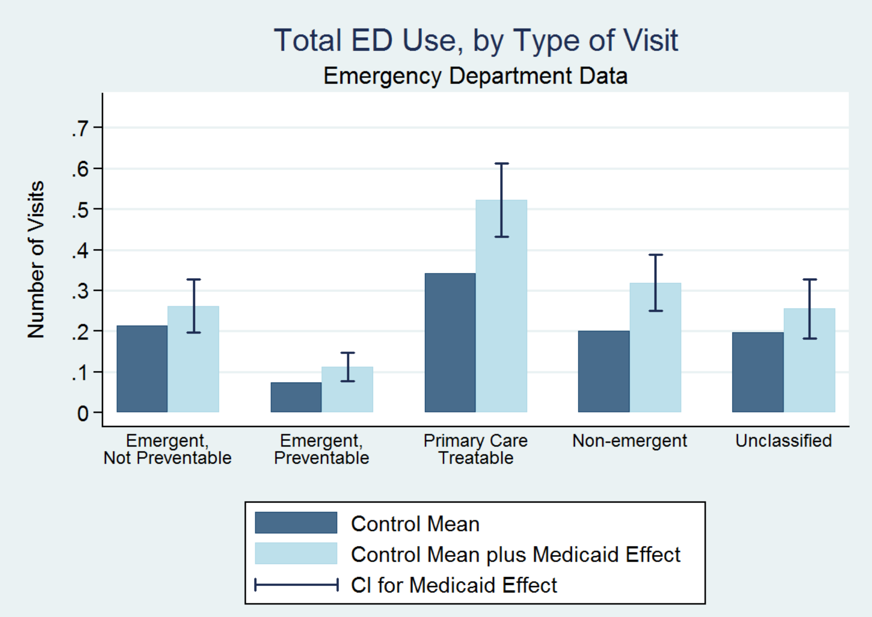
Hospitalization Utilization Increases (QJE, 2012)



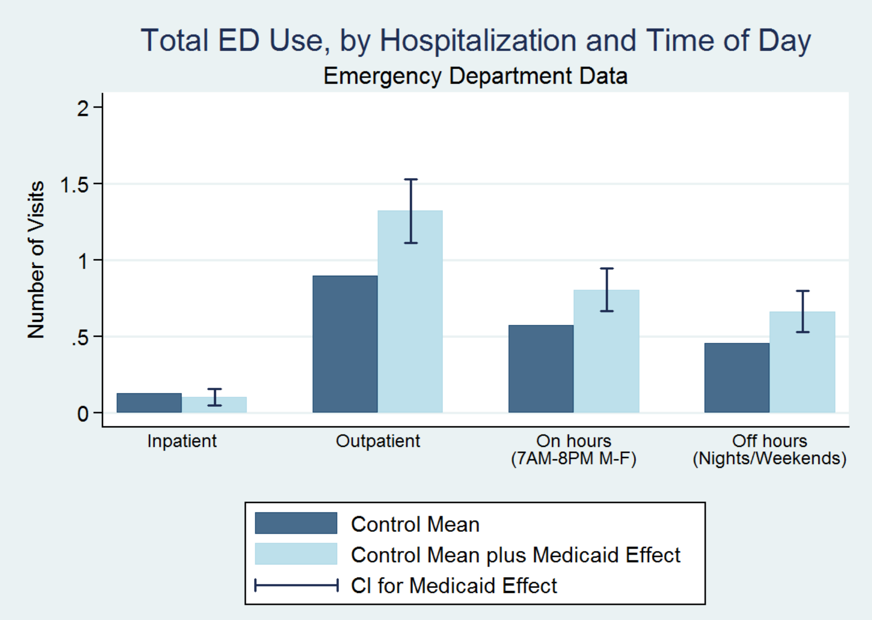
Emergency Department Use (Science, 2014)



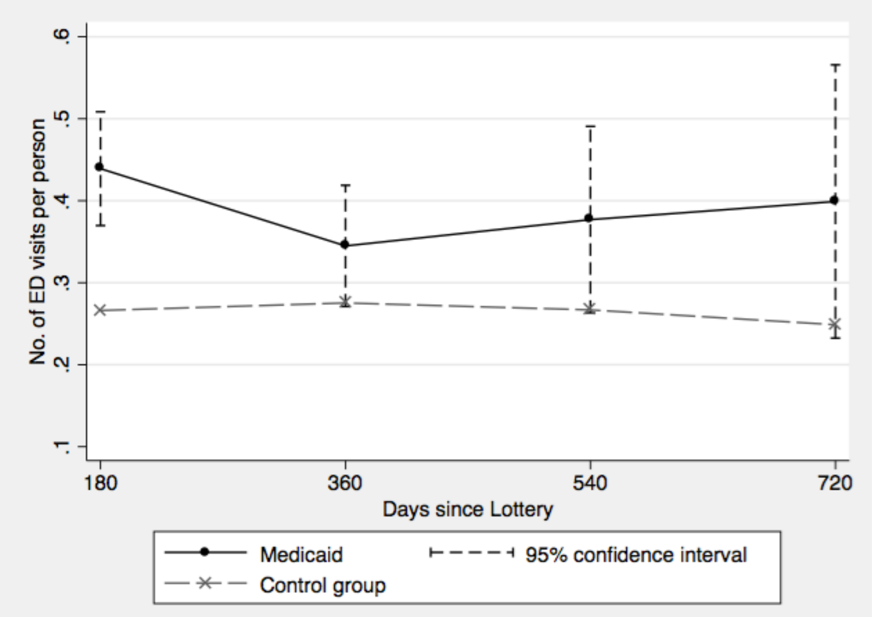
Emergency Department Use (Science, 2014)



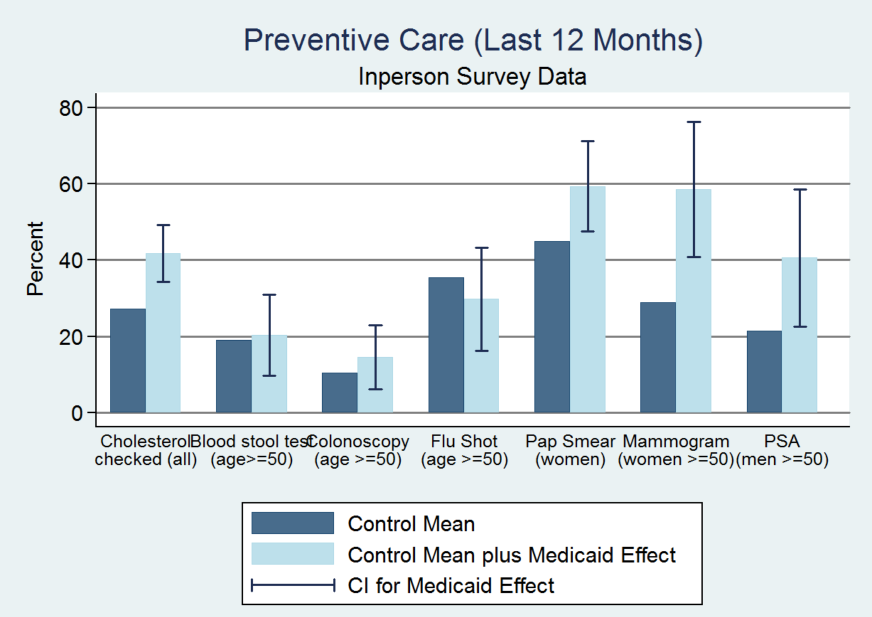
Emergency Department Use (Science, 2014)



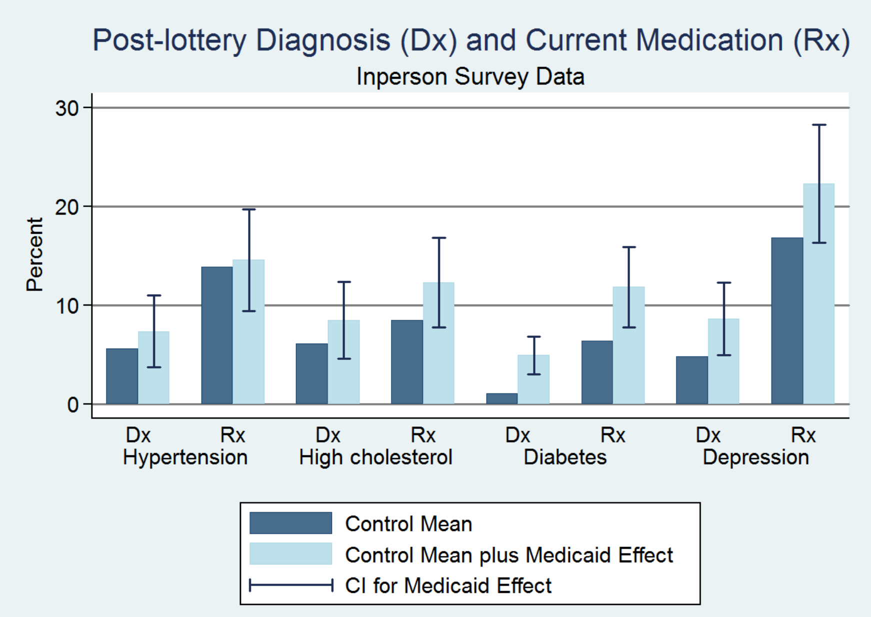
Emergency Department Use (NEJM, 2016)



Preventative Care (NEJM, 2013)



Diabetes Diagnosis (NEJM, 2013)



Utilization Summary

- Increases in healthcare utilization across the board
  - ED use goes up (contrary to some theories)
  - Preventative care increases
  - Increased diagnosis of diabetes
- What about financial strain?

Oregon Health Insurance Experiment

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)	

Oregon Health Insurance Experiment

TABLE VIII

FINANCIAL STRAIN (SURVEY DATA)

	Control mean (1)	ITT (2)	LATE (3)	*p*-values (4)
Any out of pocket medical expenses, last six months	0.555	−0.058	−0.200	[<0.0001]
	(0.497)	(0.0077)	(0.026)	{<0.0001}
Owe money for medical expenses currently	0.597	−0.052	−0.180	[<0.0001]
	(0.491)	(0.0076)	(0.026)	{<0.0001}
Borrowed money or skipped other bills to pay medical bills, last six months	0.364	−0.045	−0.154	[<0.0001]
	(0.481)	(0.0073)	(0.025)	{<0.0001}
Refused treatment because of medical debt, last six months	0.081	−0.011	−0.036	[0.01]
	(0.273)	(0.0041)	(0.014)	{0.01}
Standardized treatment effect		−0.089	−0.305	[<0.0001]
		(0.010)	(0.035)	

Oregon Health Insurance Experiment

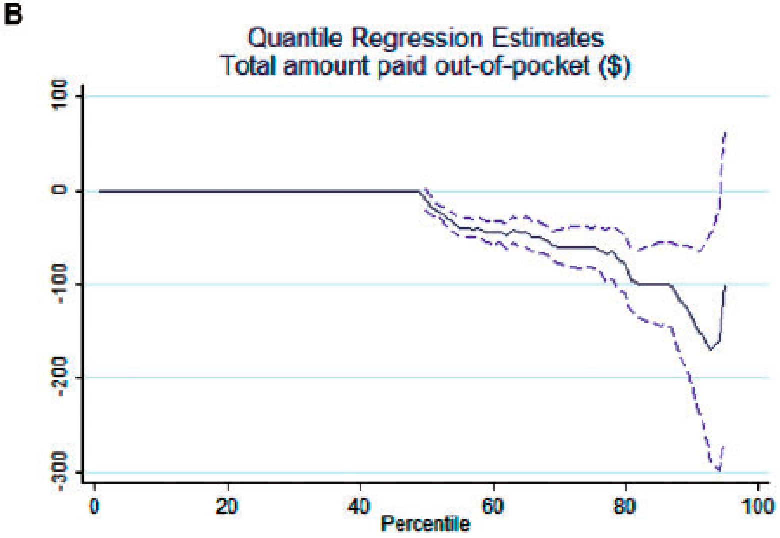
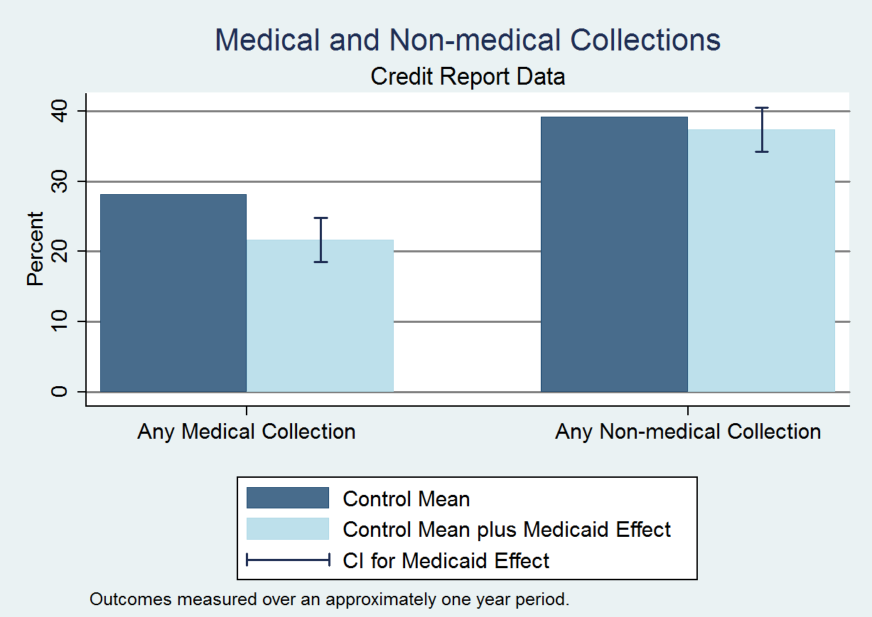
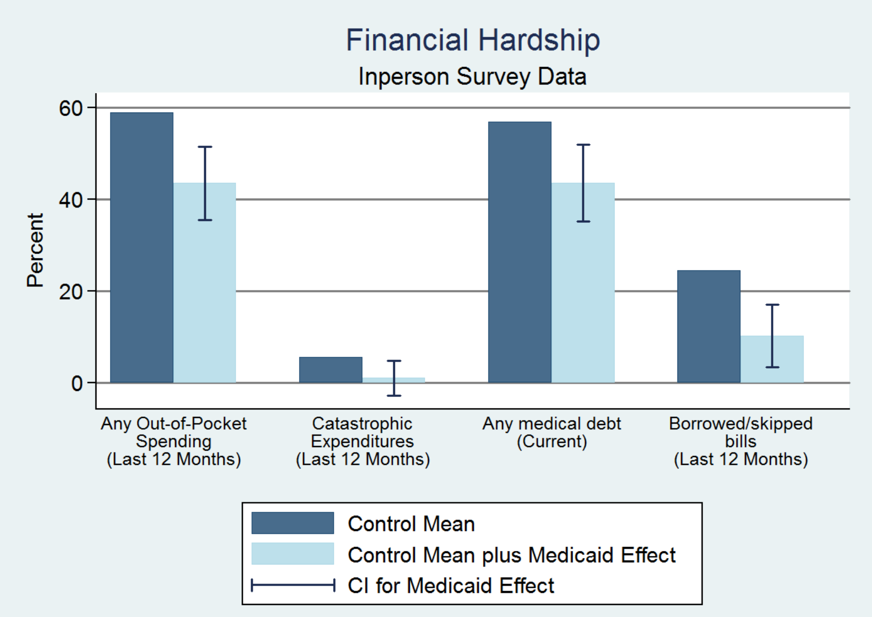


FIGURE I

Reduction in Collections (QJE, 2012)



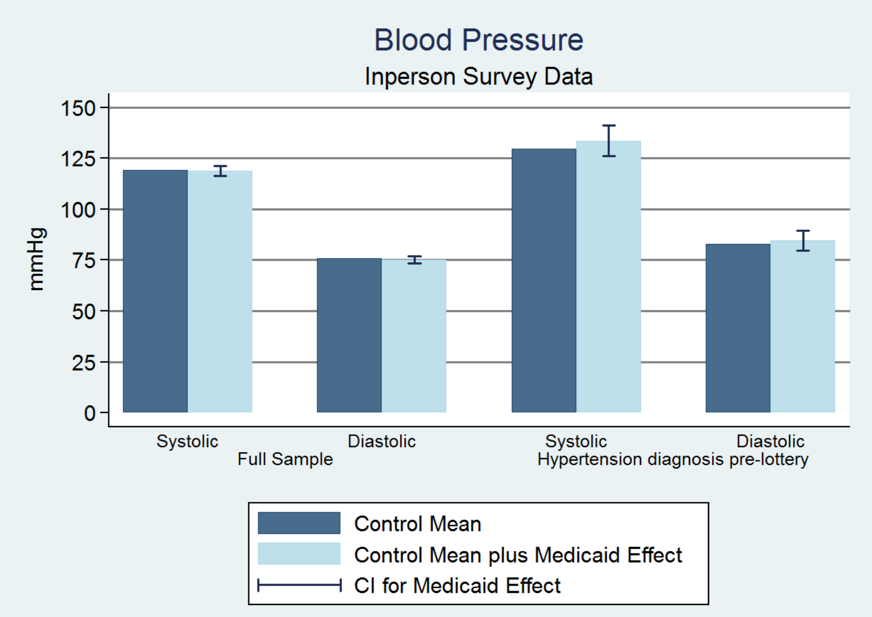
Reduction in Self-Reported Hardship (NEJM, 2013)



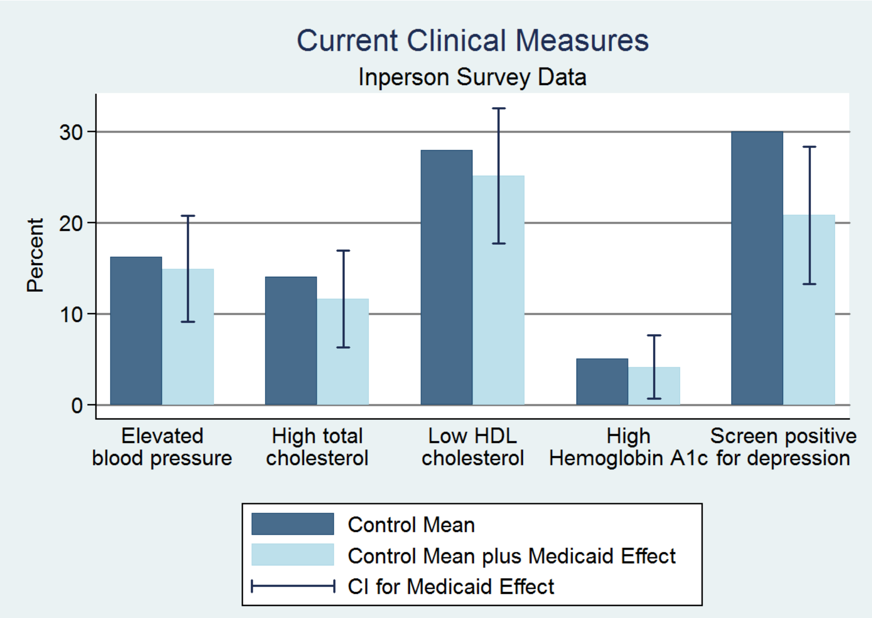
Financial Strain Summary

- Robust evidence that Medicaid reduces financial strain
  - Lower OOP spending
  - Fewer bankruptcies
  - Fewer collections
  - etc...
- What about health outcomes?

No change in blood pressure (NEJM, 2013)



Some reductions in depression (NEJM, 2013)



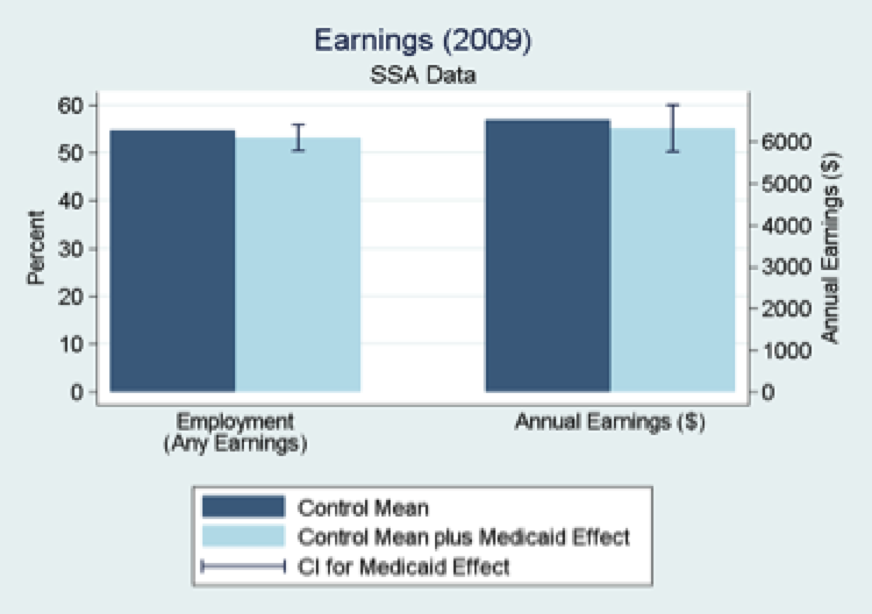
Health Impacts Summary

- Some evidence of increased subjective well-being and reduced depression
- But, no statistically significant change in medical conditions
  - Lack of power?
  - Also can't reject clinical trial estimated impact on outcomes

Medicaid and Fiscal Externalities

- What about impacts on labor supply and other program participation?
  - Why do we care?
  - Fiscal externality...
- Is the LATE what we want?
  - What about ex-ante responses?

Impacts on Earnings (AER, P&P 2014)



Medicaid on Labor Supply

Table 1: 2009 Earnings

	Control Mean (1)	ITT (2)	LATE (3)	p-values (4)
Employment (Any Earnings)	0.547	-0.0042 (0.0037)	-0.016 (0.014)	0.266
Amount of Earnings	6513.015 (10227.3)	-51.74 (76.8)	-194.93 (289.0)	0.500
Earnings above FPL	0.131	-0.0032 (0.0026)	-0.012 (0.0099)	0.219

Medicaid on Labor Supply

Table 2: 2009 Benefits

	I. Any Receipt of Benefits				II. Amount of Benefits Received			
	Control Mean	ITT	LATE	p-values	Control Mean	ITT	LATE	p-values
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Food Stamps (SNAP)	0.599	0.025	0.095	<.001	1494.346	72.75	276.19	<.001
		(0.0038)	(0.014)		(1893)	(15.75)	(58.85)	
TANF	0.031	0.0031	0.012	0.042	111.363	2.62	9.89	0.659
		(0.0015)	(0.0058)		(711)	(5.94)	(22.43)	
SSI	0.050	-0.00024	-0.00092	0.888	30.626	0.25	0.93	0.821
		(0.0017)	(0.0065)		(137.972)	(1.08)	(4.09)	
SSDI	0.084	0.0017	0.0066	0.222	943.189	14.43	54.41	0.405
		(0.0014)	(0.0054)		(3401.323)	(17.33)	(65.31)	

Note: All outcomes are measured at the individual level except for "Amount of TANF" and "Amount of SNAP" which are the amount that the individual's household received. Columns (1) & (5) report the control mean of the dependant variable and standard deviation for continuous outcomes (in parentheses). Columns (2) and (6) reports coefficient (and standard error in parentheses) on LOTTERY from estimating equation (1) by OLS; columns (3) and (7) reports coefficient (and standard error in parentheses) on MEDICAID from estimating equation (2) by IV. Column (4) reports the p-values. All regressions control for dummies for number of household members on the lottery list and the 2007 value of the dependent variable. Standard errors are clustered by household. All regressions are weighted to adjust for a new lottery that started in late 2009. N=61790.

Welfare Relevance of Program Participation Effects?

- Medicaid Lottery increases Food Stamp enrollment
  - What is the welfare impact?
- Information versus price effects
  - If people learned from their doctor or other program officer that they were eligible for other benefits beyond Medicaid, can generate first order welfare benefit from changing behavior in response to this information
- Labor supply didn't change -> eligibility didn't change; only enrollment?
  - Was it information?

Beyond Oregon: Impacts on Financial Strain

- MA health insurance expansion required everyone to obtain insurance
- Impact on financial strain: Mazumder and Meyer (2016)
- Study county-level credit records in MA
  - Look at heterogeneity as function of %uninsured prior to MA reform

Mazumder and Meyer (2016)

$$(1) \quad Y_{cat} = \beta_{ca} + \sum_{y=1999}^{2012} \Big(\beta_{y1} \times I(Year = y) + \beta_{y2} Uninsured2005_{ca} \times I(Year = y) + \beta_{y3} MA_c \times I(Year = y) + \beta_{y4} MA_c \times Uninsured2005_{ca} \times I(Year = y)\Big) + \epsilon_{cat},$$

Mazumder and Meyer (2016)

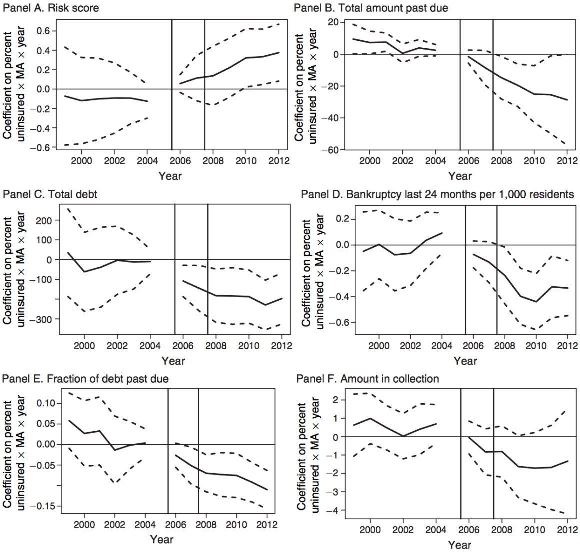


FIGURE 4. COEFFICIENT ON *PercentUninsured* × *MA* × *Year* BY YEAR

Uncompensated Care

- Health insurance expansions reduce bankruptcy and unpaid bills
  - Implies beneficiaries of public health insurance are not necessarily the beneficiaries themselves
- Garthwaite, Gross, and Notowidigdo (2015): "Hospitals as Insurers of Last Resort"
  - Document significant impact of public health insurance on reductions in other forms of charity care and uncompensated care
- Use two empirical strategies:
  - Panel regression of uncompensated care cost on %uninsured
    - Control for state and year effects
  - Large dis-enrollment in Tennessee and Missouri Medicaid program from funding reduction

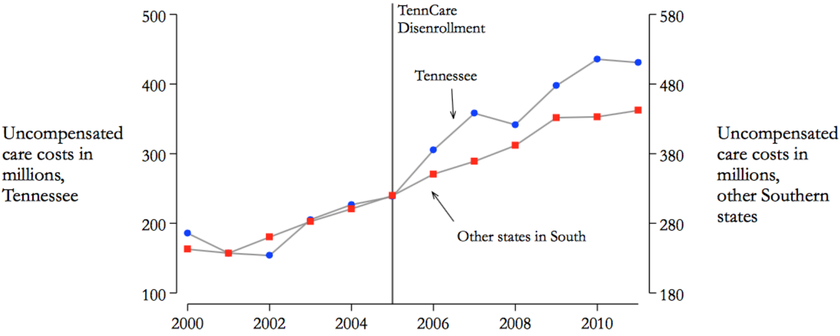
Garthwaite, Gross, and Notowidigdo (2015)

Table 2. Effect of Uninsured Population on Uncompensated Care at All Hospitals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Per-capita uncompensated care				Uncompensated care divided by expenditures			
				A. All Hospitals				
Share of population uninsured	856.49	880.95	903.27	887.27	0.18	0.17	0.17	0.16
	(309.58)	(303.96)	(344.80)	(307.20)	(0.05)	(0.05)	(0.05)	(0.05)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
R^2	0.871	0.873	0.890	0.893	0.825	0.828	0.860	0.864
N	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224
				B. Hospitals with an ED				
Share of population uninsured	863.05	886.42	910.39	892.36	0.19	0.18	0.18	0.16
	(317.77)	(312.96)	(358.81)	(320.36)	(0.05)	(0.05)	(0.05)	(0.05)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
R^2	0.865	0.867	0.885	0.888	0.820	0.822	0.858	0.862
N	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224
				C. Hospitals without an ED				
Share of population uninsured	- 6.85	- 5.88	- 8.46	- 6.50	0.00	0.00	0.01	0.01
	(11.38)	(12.07)	(17.95)	(17.64)	(0.04)	(0.04)	(0.05)	(0.05)
	[0.55]	[0.63]	[0.64]	[0.71]	[1.00]	[0.98]	[0.91]	[0.81]
R^2	0.480	0.481	0.549	0.551	0.294	0.295	0.389	0.390
N	1,200	1,200	1,200	1,200	1,200	1,200	1,200	1,200
				D. Acute-Care Hospitals with an ED				
Share of population uninsured	863.05	886.42	910.39	892.36	0.19	0.18	0.18	0.16
	(317.77)	(312.96)	(358.81)	(320.36)	(0.05)	(0.05)	(0.05)	(0.05)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
R^2	0.865	0.867	0.885	0.888	0.820	0.822	0.858	0.862
N	1,224	1,224	1,224	1,224	1,224	1,224	1,224	1,224
State-year controls		✓		✓		✓		✓
Region-year fixed effects			✓	✓			✓	✓

Garthwaite, Gross, and Notowidigdo (2015)

Figure 3. Uncompensated Care Costs in Tennessee



Note: This figure presents total uncompensated care costs in Tennesse versus other Southern states, as reported in the AHA survey. See text for details.

Garthwaite, Gross, and Notowidigdo (2015)

- Greater uninsured lead to greater uncompensated care paid by hospitals
    - Implies beneficiaries of public health insurance are not necessarily the beneficiaries themselves
- Estimates suggest each additional uninsured person costs local hospitals $900 each year in uncompensated care

Miller, Altekruse, Johnson, and Wherry (2019)

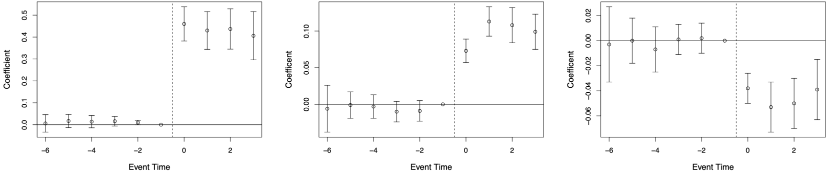
- Miller et al (2019) conduct difference in difference using Medicaid expansion states as a source of variation
- Analyze impact on adult mortality rate using SSA Numident
  - Linked to ACS

$$Died_{isjt} = Expansion_s \times \sum_{\substack{y=-6 \\ y \neq -1}}^{3} \beta_y I(t - t_s^* = y) + \beta_t + \beta_s + \beta_j + \gamma \mathbf{I}(j = t) + \epsilon_{isjt}. \quad (1)$$

As described earlier, our data is constructed at the individual (i) by year (t) level. Each individual responds to the ACS during a survey wave (j) and reports their state of residence (s). The dependent variable $Died_{isjt}$ denotes death during each year t among individuals who were alive at the beginning of year t. We only observe mortality over a partial year during the year of the individual's ACS interview

Miller, Altekruse, Johnson, and Wherry (2019)

Figure 1: Effect of the ACA Medicaid Expansions on Eligibility and Coverage

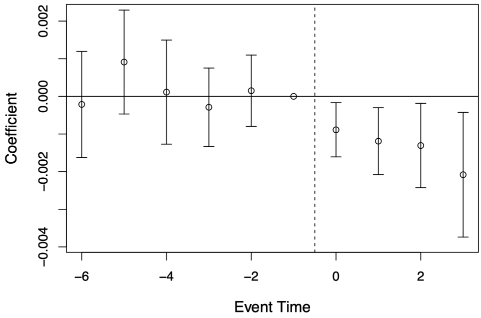


(a) Medicaid Eligibility (b) Medicaid Coverage (c) Uninsured

Note: These figures report coefficients from the estimation of equation (1) for the outcomes of Medicaid eligibility, Medicaid coverage, and uninsurance in the 2008-2017 American Community Survey. Note that scales differ across the three figures. The coefficients represent the change in outcomes for expansion states relative to non-expansion states in the six years before and four years after expansion, as compared to the year immediately prior to the expansion. The sample is defined as U.S. citizens ages 55-64 in 2014 who are not SSI recipients and who have either less than a high school degree or household income below 138% FPL. See Appendix Section B for detailed information on Medicaid eligibility determination.

Miller, Altekruse, Johnson, and Wherry (2019)

Figure 2: Effect of the ACA Medicaid Expansions on Annual Mortality

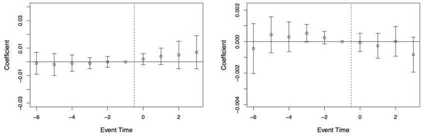


Note: This figure reports coefficients from the estimation of Equation 1 for annual mortality. The coefficients represent the change in mortality for expansion states relative to non-expansion states in the six years before and four years after expansion, as compared to the year immediately prior to the expansion. The sample is defined as U.S. citizens ages 55-64 in 2014 observed in the 2008-2013 American Community Survey who are not SSI recipients and who have either less than a high school degree or household income below 138% FPL.

Miller, Altekruse, Johnson, and Wherry (2019)

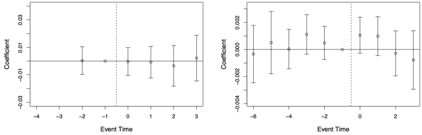
Figure 3: Placebo Tests

Age 65+ in 2014



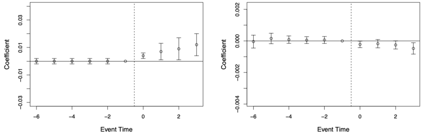
(a) Medicaid Coverage (b) Annual Mortality

Pre-ACA Years



(c) Medicaid Coverage (d) Annual Mortality

Income 400%FPL +



(e) Medicaid Coverage (f) Annual Mortality

Note: These figures plot coefficients from equation (1) for those age 65 and older in 2014 who would not have been

Informal Welfare Analysis

- Media:
  - *"Medicaid Makes 'Big Difference' in Lives, Study Finds"*
    - National Public Radio (2011)
  - *"Spending on Medicaid Doesn't Actually Help the Poor"*
    - Washington Post (2013)
- Public policy centers:
  - *"Oregon's lesson to the nation: Medicaid Works"*
    - Oregon Center for Public Policy (2013)
  - *"Oregon Medicaid Study Shows Michigan Medicaid Expansion Not Worth the Cost"*
    - MacKinac Center for Public Policy (2013)

Welfare Analysis

- Present results from two recent approaches:
- "Model-based" approach in Finkelstein, Hendren, and Luttmer (2016)
  - Conduct welfare analysis of Oregon Health Insurance Experiment
- "Revealed-preference" approach in Finkelstein, Hendren, and Shepard (2017)

Model-Based Approach: Two Frameworks

1. Complete-information approach
   - Completely specify normative utility function and estimate causal effect of Medicaid on distribution of all utility-relevant arguments
     - Here: Consumption and Health
   - Don't need to assume consumer optimization or need to model how Medicaid affects budget set
2. Optimization approaches
   - Assume consumer optimization
   - Model how Medicaid affects the budget set (in each state of the world)
   - Only specify marginal utility function over one argument
   - Implement three versions:
     - Consumption-Based Optimization Approach using "consumption proxy"
     - Consumption-Based Optimization Approach using "CEX data"
     - Health-Based Optimization Approach

Setup (common to both frameworks)

- Individuals derive utility from health, h, and consumption of non-medical goods and services, c

$$u = u(c, h)$$

- Health h produced according to $h = \tilde{h}(m; \theta)$
  - Medical spending, m
  - θ denotes underlying state variable
    - medical conditions, other factors affecting health, etc.
- Assume each Medicaid recipient faces same distribution of θ
  - Conceptually: welfare analysis behind behind veil of ignorance
  - Empirically: cross-sectional distribution of outcomes capture different potential θ
  - Presence of Medicaid denoted by $q \in \{0, 1\}$

Complete-Information Approach

- Define $c(q;\theta)$, $h(q;\theta)$, and $m(q;\theta)$ to be distributions of consumption, health, and medical spending conditional on insurance q

- Define welfare impact of Medicaid on recipient, $\gamma(1)$:

$$E\left[u\left(c\left(0;\theta\right),h\left(0;\theta\right)\right)\right]=E\left[u\left(c\left(1;\theta\right)-\gamma(1),h\left(1;\theta\right)\right)\right]$$

  - Expectations taken over all possible states of world θ

- To recover $\gamma(1)$ from above equation requires:
  - Estimates of distribution of c and h at $q=1$ and $q=0$
  - Specification of normative utility function over *all* its arguments (in our application: c, h)

Complete-Information Approach: Implementation

- **Assumption 1:** Full specification of utility function:

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

- $\gamma(1)$ solves:

$$E\left[\frac{c\left(0;\theta\right)^{1-\sigma}}{1-\sigma}+\phi h\left(0;\theta\right)\right]=E\left[\frac{\left(c\left(1;\theta\right)-\gamma\left(1\right)\right)^{1-\sigma}}{1-\sigma}+\phi h\left(1;\theta\right)\right]$$

- Requirements:
  - Causal effects on distribution of c and mean h for $q=0$ and $q=1$
  - Full specification of normative utility function

Optimization Approaches: Model Program Structure

- Reduce information requirements through additional assumptions
- **Assumption 2:** (Program structure) Medicaid's only direct effect is on the out-of-pocket price for medical care, $p(q)$
  - Rules out other ways Medicaid might affect consumption or health
  - E.g., impacts on provider behavior
- Implementation: define out-of-pocket spending, x, for medical care by:

$$x(q, m) \equiv p(q)m$$

Assumption 3: Individual Optimization

- **Assumption 3:** Individuals choose m and c optimally, subject to their budget constraint

$$\max_{c,m} u\left(c, \tilde{h}\left(m;\theta\right)\right) \text{ subject to } c = y\left(\theta\right) - x\left(q, m\right) \quad \forall m, q, \theta.$$

  - $y(\theta)$ denotes (potentially state-contingent) income plus any (potentially state-contingent) changes in assets (savings or borrowings)

- Not an innocuous assumption in health care context!
  - Decisions are taken jointly with other agents (e.g., doctors) who may have different objectives (e.g., Arrow 1963)
  - Complex nature of decision may generate individually sub-optimal behavior

Thought Experiment: Marginal Expansion of Medicaid

- Let $q \in [0,1]$ trace a "marginal" expansion in Medicaid:
  $$x(q,m) = (1-q)p(0)m + qp(1)m$$
- Marginal expansion of Medicaid (marginal increase in q), relaxes the individuals budget constraint by $-\frac{\partial x}{\partial q}$:
  $$-\frac{\partial x(q, m(q;\theta))}{\partial q} = (p(0) - p(1))m(q;\theta)$$
  - Note: this is program parameter (i.e., holding behavior, m, constant)
- Value to recipient of getting fraction q of Medicaid is given by $\gamma(q)$:
  $$E\left[u\left(c\left(0;\theta\right), h\left(0;\theta\right)\right)\right] = E\left[u\left(c\left(q;\theta\right) - \gamma(q), h\left(q;\theta\right)\right)\right]$$

Consumption-Based Optimization Approach

Use envelope theorem to derive value of marginal expansion of insurance:

$$\frac{d\gamma}{dq} = E\left[\underbrace{\frac{u_c}{E\left[u_c\right]}}_{\substack{\text{Relative}\\ \text{marginal utility}}} \times \underbrace{(p(0) - p(1))m(q;\theta)}_{\substack{\text{Marginal relaxation of}\\ \text{budget constraint: } -\partial x/\partial q}} \right]$$

- Value budget constraint relaxation by $\frac{u_c}{E[u_c]}$ in each state, θ
- Because derivation is based on envelope theorem, we do not require first-order condition to hold everywhere (i.e., medical spending can be "lumpy")

Consumption-Based Optimization Approach

- Decompose $\frac{d\gamma(q)}{dq}$ into a transfer term and a pure-insurance term
  - Implementation will be based on estimating each term separately

$$\frac{d\gamma(q)}{dq} = \underbrace{(p(0)-p(1))E[m(q;\theta)]}_{\text{Transfer Term}} + \underbrace{Cov\left[\frac{u_c}{E[u_c]},(p(0)-p(1))m(q;\theta)\right]}_{\substack{\text{Pure-Insurance Term} \\ \text{(consumption valuation)}}}$$

- Transfer term: Value to beneficiary of expected resource transfers from rest of economy
  - Medical spending times change in out-of-pocket price
- Pure-insurance term: Value of reallocating resources (by relaxing budget constraint) across different states of world
  - Medicaid adds value if it moves resources from states of the world with lower marginal utility of consumption into states of the world with higher marginal utility

Consumption-Based Optimization Approach

- To arrive at non-marginal estimate, integrate over q :

$$\gamma(1) = \int_0^1 \frac{d\gamma(q)}{dq} dq =$$

$$\underbrace{(p(0)-p(1)) \int_0^1 E[m(q;\theta)] dq}_{\text{Transfer Term}} + \underbrace{\int_0^1 Cov\left(\frac{u_c}{E[u_c]}, (p(0)-p(1)) m(q;\theta)\right) dq}_{\substack{\text{Pure-Insurance Term} \\ \text{(consumption valuation)}}}$$

- The transfer term does not depend on the utility function
  - therefore relatively straightforward to implement
  - same for all optimization approaches (whether consumption based or health based)

Implementation: Pure-Insurance Term

- Requires *partial* specification of utility function: only marginal utility of consumption
- **Assumption 4**: Utility function has the form:

$$u(c, h, .., ..) = \frac{c^{1-\sigma}}{1-\sigma} + v(h, .., ..)$$

  - where $v(.)$ is unspecified subutility function over health and any other arguments of the utility function
- As a result, can write the pure-insurance term as:

$$\underbrace{Cov\left[\frac{u_c}{E\left[u_c\right]}, (p(0) - p(1))m(q;\theta)\right]}_{\substack{\text{Pure-Insurance Term} \\ \text{(consumption valuation)}}} = Cov\left(\frac{c\left(q;\theta\right)^{-\sigma}}{E\left[c\left(q;\theta\right)^{-\sigma}\right]}, (p(0) - p(1))m(q;\theta)\right)$$

Implementation: Interpolation

- Only observe q at 0 and at 1.
- Need additional assumption to obtain $\gamma(1)$
  - Baseline: statistical assumption: $\frac{d\gamma}{dq}$ linear in q
  - Explore sensitivity to alternatives (e.g., m linear in q, or m as *any* increasing function of q, bounds on transfer term)
- **Assumption 5**: Linear approximation:

$$\gamma(1) \approx \frac{1}{2}\left[\frac{d\gamma(0)}{dq} + \frac{d\gamma(1)}{dq}\right]$$

- Compare to complete-information approach which can deliver non-marginal welfare estimates directly

Baseline Estimates, $\gamma(1)$

Table 2: Welfare Benefit Per Recipient

	I	II	III	IV
	Complete-Information Approach (Consumption Proxy)	Optimization Approaches		
		Consumption-Based (Consumption Proxy)	Consumption-Based (CEX Cons. Measure)	Health-Based
A. Welfare Effect on Recipients, $\gamma(1)$	1675	1421	793	690
(standard error)	(60)	(180)	(417)	(420)
Transfer component, T	699	661	661	661
Pure-insurance component, I	976	760	133	30

Notes: Estimates of welfare effects and moral hazard costs are expressed in dollars per year per Medicaid recipient. Standard errors are bootstrapped with 500 repetitions.

Benchmarks

- G is cost to Government of providing Medicaid:

$$G = E\left[m\left(1;\theta\right)\right] = \$3,600$$

- N is monetary transfer by Medicaid to external parties:

$$N = E\left[m\left(0;\theta\right)\right] - E\left[x\left(0, m(0;\theta)\right)\right] = \$2,721 - \$569 = \$2,152$$

- C is *net* resource cost of Medicaid $= G - N =$ increase in m plus decrease in x:

$$C = G - N = \$3,600 - \$2,152 = \$1,448$$

Comparisons

Table 2B: Comparisons

	I	II	III	IV
	Complete-Information Approach (Consumption Proxy)	Optimization Approaches		
		Cons.-Based (Consumption Proxy)	Cons.-Based (CEX Cons. Measure)	Health-Based
A. Welfare Effect on Recipients, $\gamma(1)$	1675	1421	793	690
B. Transfer to External Parties, N	2152	2152	2152	2152
C. Efficiency				
Pure-insurance component, I	976	760	133	30
Moral hazard cost, G-N-T = C - T	749	787	787	787
D. Ratios of $\gamma(1)$ relative to:				
monetary transfer to external parties, $\gamma(1)/N$	0.78	0.66	0.37	0.32
net costs, $\gamma(1)/C$	1.16	0.98	0.55	0.48
gross costs, $\gamma(1)/G$	0.47	0.39	0.22	0.19

Key Findings From Baseline Specifications, I

- First two key findings:
  1. Recipients' value from Medicaid is 1/3 to 3/4 of transfers to external parties, $\gamma(1) < N$
  2. Cash vs. In-kind: Recipients would rather give up Medicaid than pay G, $\gamma(1) < G$

- Driven by substantial transfers to external parties ($N/G = 0.6$).
  - Uninsured pay only about $0.20 on the dollar for medical spending
  - Consistent with other estimates of share of medical expenses paid by uninsured (e.g., Coughlin et al., 2014; estimates in MEPS)
  - Consistent with other evidence of implicit insurance
    - Medicaid substantially reduces provision of uncompensated care by hospitals (Garthwaite et al. 2015)
    - Impact of health shocks on access to credit similar for insured and uninsured (Dobkin et al. 2015)

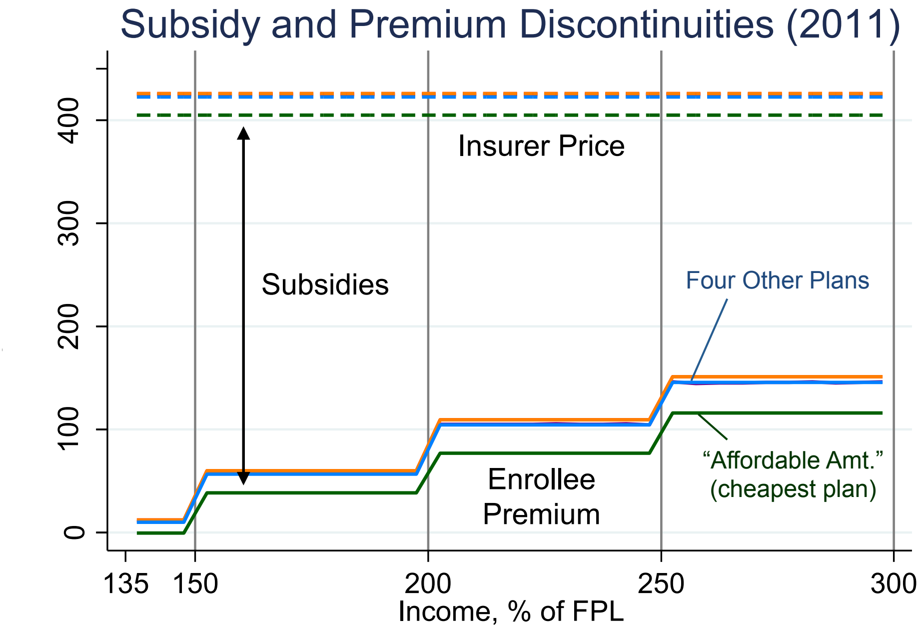
  - Key question: economic incidence of transfers to external parties

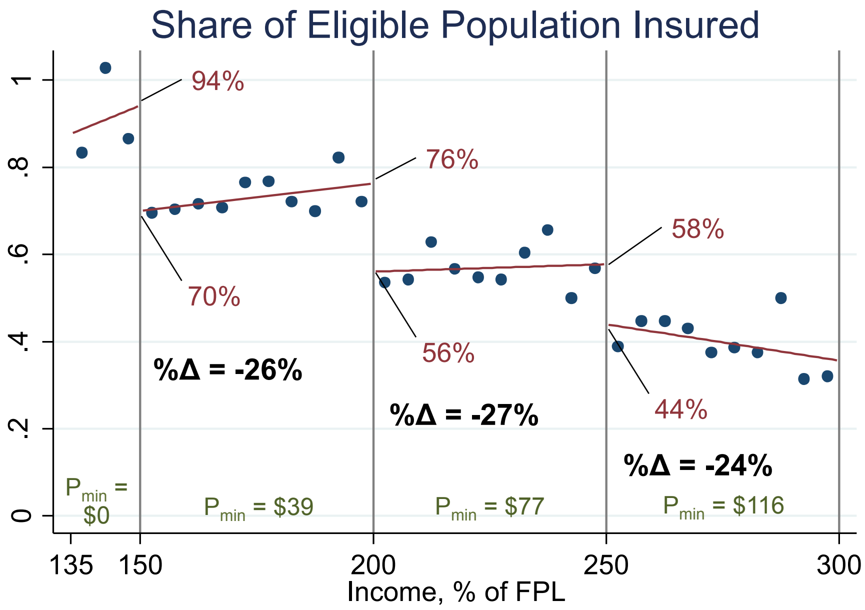
Summary

- Key limitation for welfare analysis of public health insurance / Medicaid: Do not observe choices
- FHL2016 impose a utility function (or coeff. of risk aversion)
  - Maybe people really are WTP more for health insurance than is generated from CRRA=3?
- Alternative: Exploit setting where we do see prices

Revealed Preference Approach

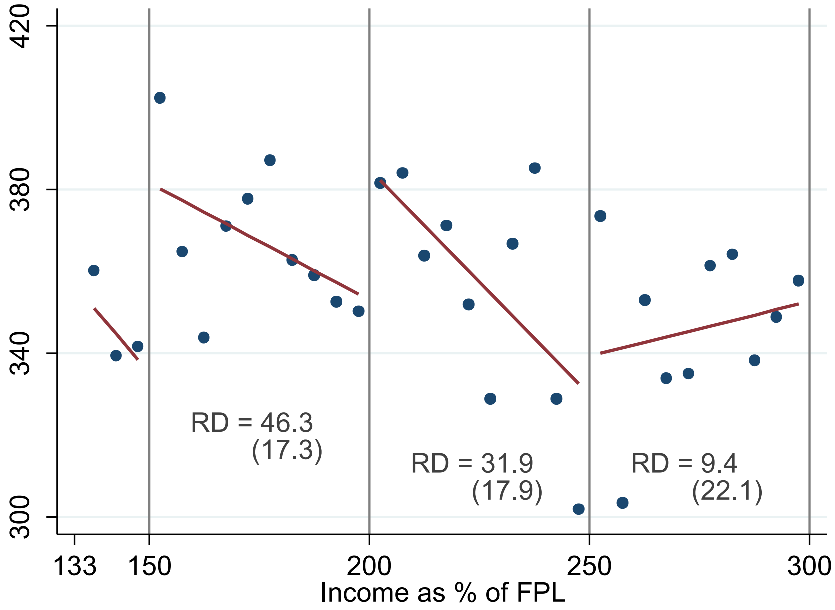
- Finkelstein, Hendren, and Shepard (2016) exploit subsidized health insurance exchange in Massachusetts (pre ACA)
  - Charged premiums that were discontinuous functions of income
- Estimate demand and cost curves for insurance
  - Idea: Enrollment on exchange reveals willingness to pay (demand)
  - Key variation: Premium discontinuities by income group
    - E.g., Cheapest plan is \$0 for 100-150% pov.; \$39 for 150-200% pov.
  - RD Strategy: Compare 149% poverty vs. 151% poverty to measure how much higher premium reduces demand, affects avg. costs
    - No evidence of income manipulation across thresholds (why is this important?)

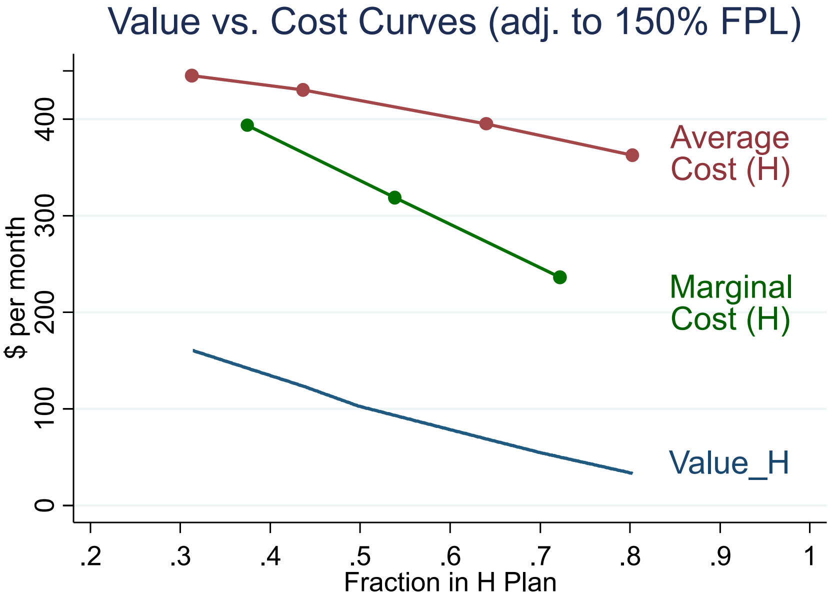

Subsidy and Premium Discontinuities (2011)
400
300
200
100
0
135
150
200
250
300
Income, % of FPL
Insurer Price
Subsidies
Four Other Plans
Enrollee
Premium
"Affordable Amt."
(cheapest plan)



Share of Eligible Population Insured
94%
76%
70%
58%
56%
44%
%Δ = -26%
%Δ = -27%
%Δ = -24%
P min = $0
P min = $39
P min = $77
P min = $116
0
.2
.4
.6
.8
1
135
150
200
250
300
Income, % of FPL

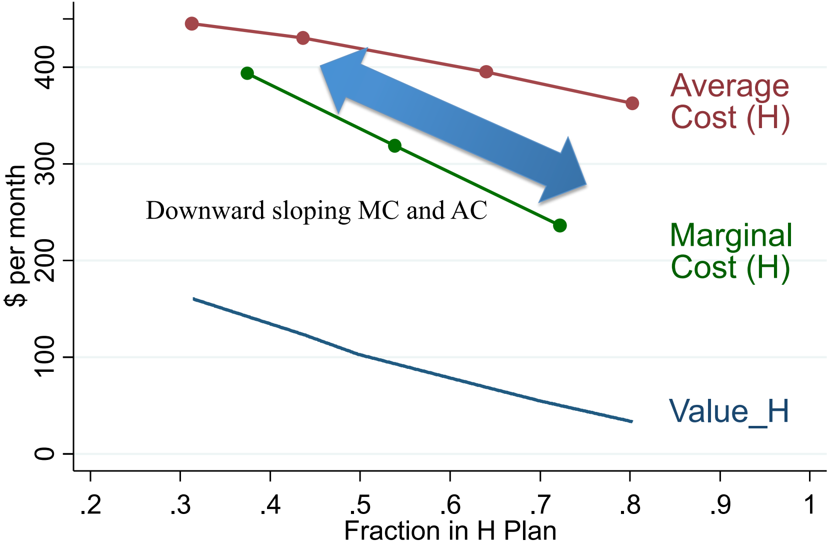
Insurer Costs



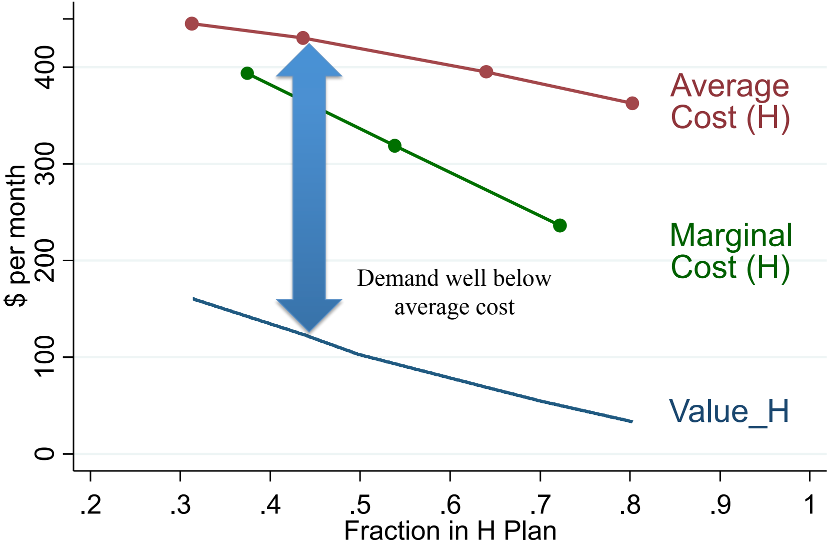


Value vs. Cost Curves (adj. to 150% FPL)
$ per month
0
100
200
300
400
.2
.3
.4
.5
.6
.7
.8
.9
1
Fraction in H Plan
Average Cost (H)
Marginal Cost (H)
Value_H

Result #1: Substantial Adverse Selection

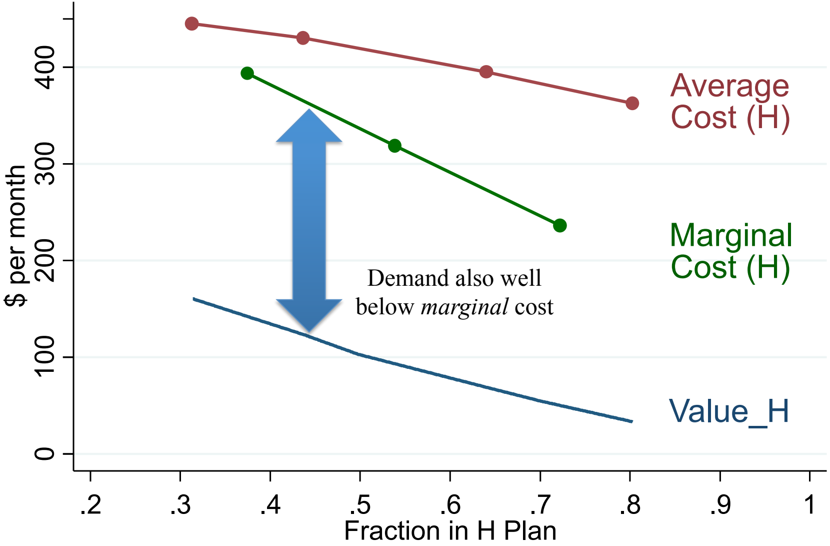


Result #2: Little Take-up w/out Large Subsidies

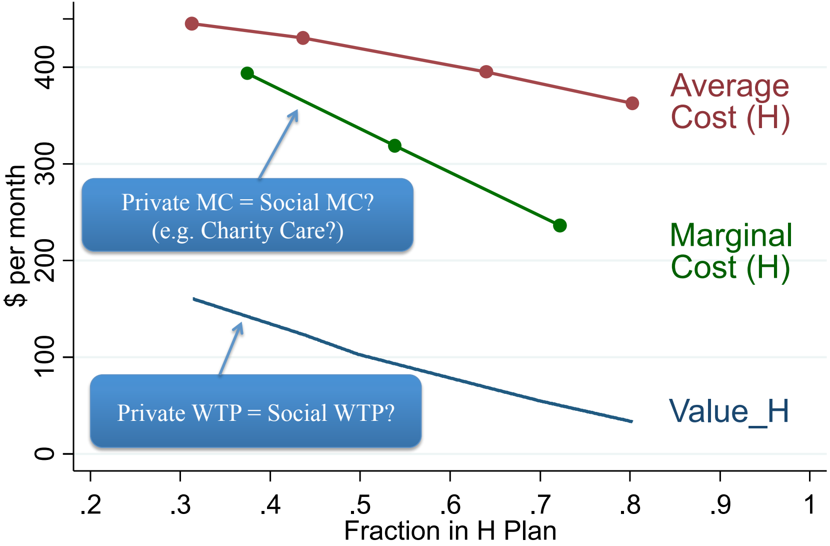


Result #3: Adverse selection alone cannot explain low covg.

Suggests most enrollees would <u>prefer cash to coverage</u>

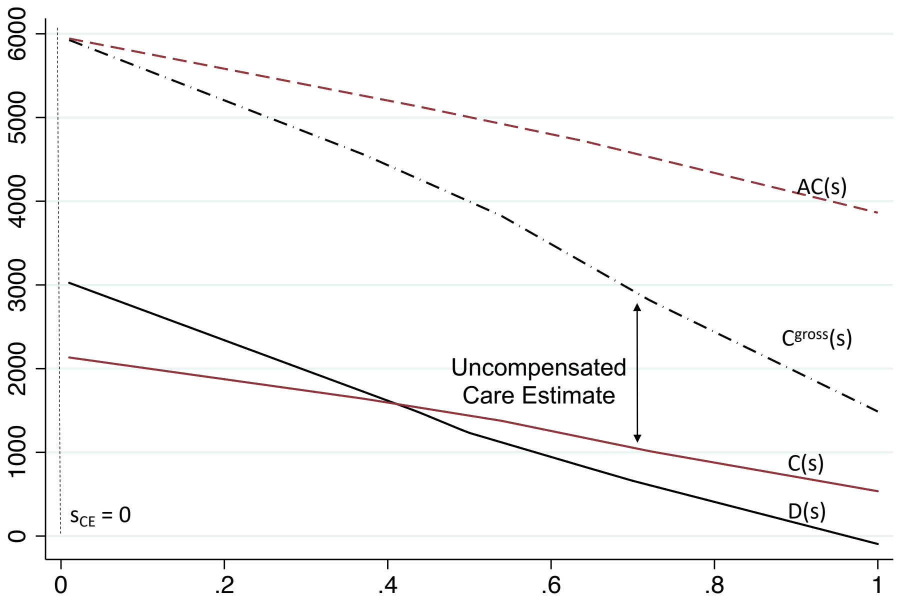


Normative Conclusions Not Immediate

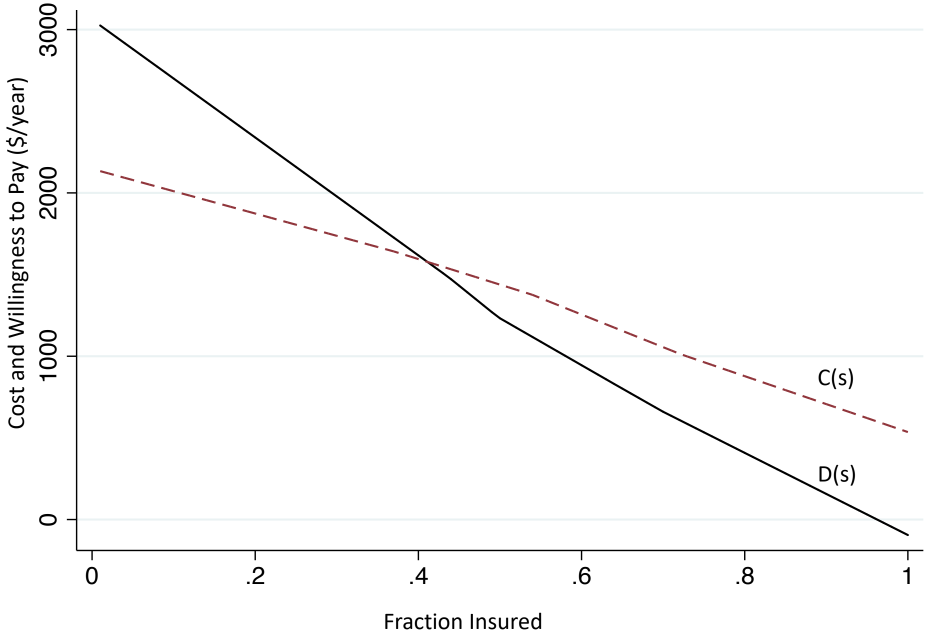


Ex-Ante WTP?

- What about ex-ante WTP we discussed last class?
- Apply approach from Hendren (2018)

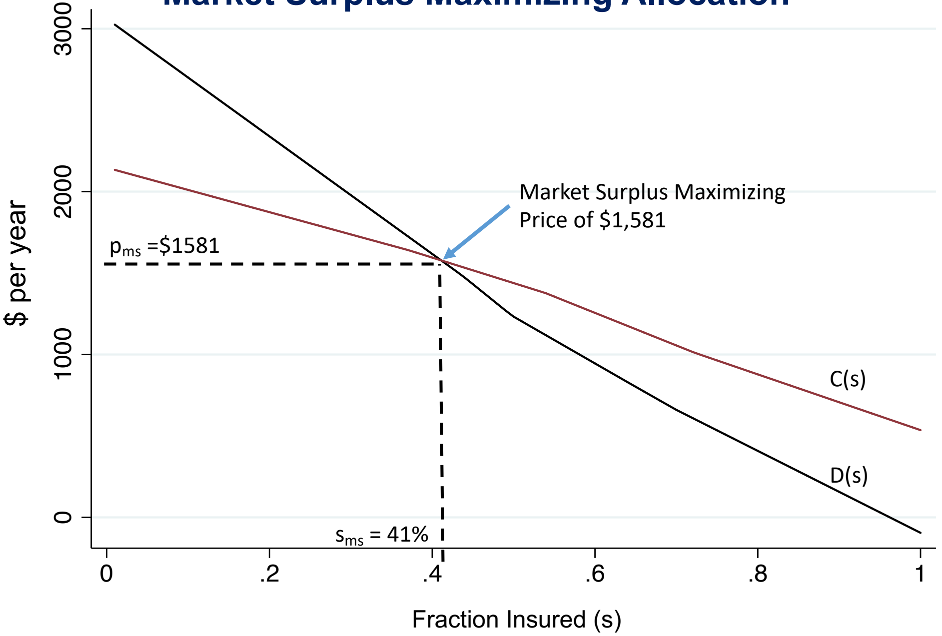


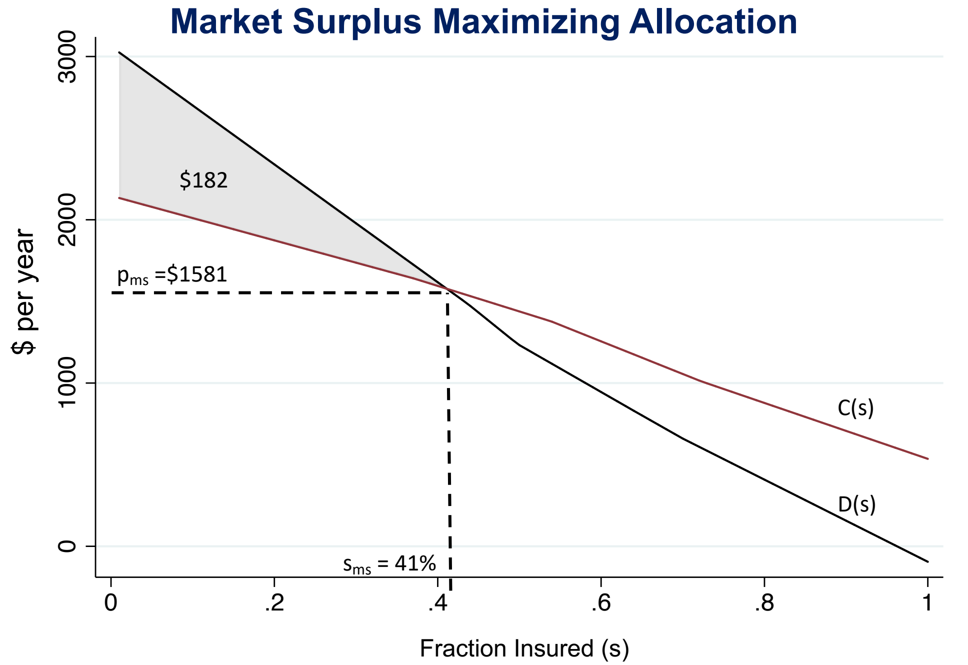
6000
5000
4000
3000
2000
1000
0
0
.2
.4
.6
.8
1
AC(s)
$C^{gross}(s)$
Uncompensated
Care Estimate
C(s)
D(s)
$s_{CE} = 0$



Cost and Willingness to Pay ($/year)
3000
2000
1000
0
C(s)
D(s)
0
.2
.4
.6
.8
1
Fraction Insured

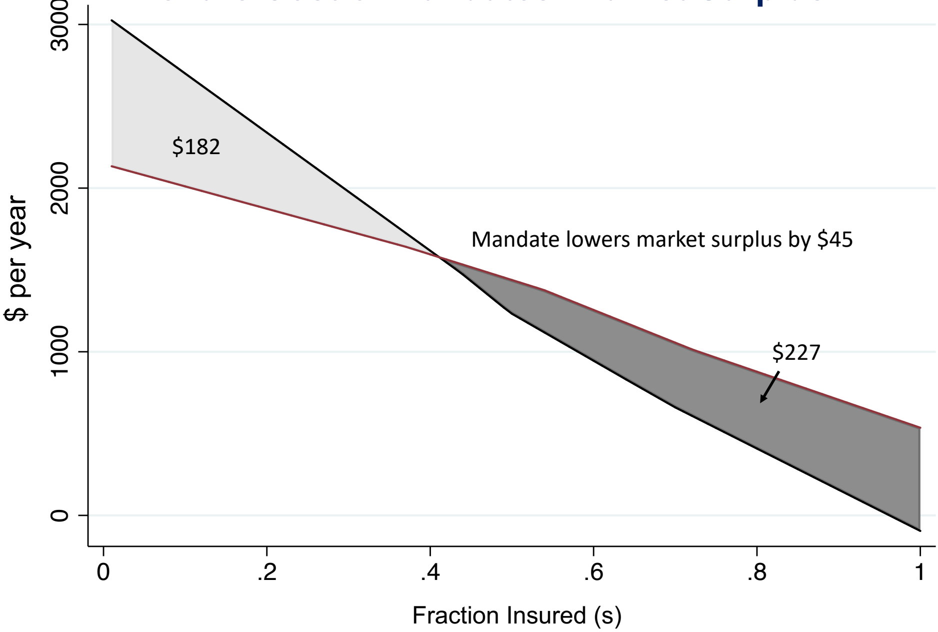
Market Surplus Maximizing Allocation

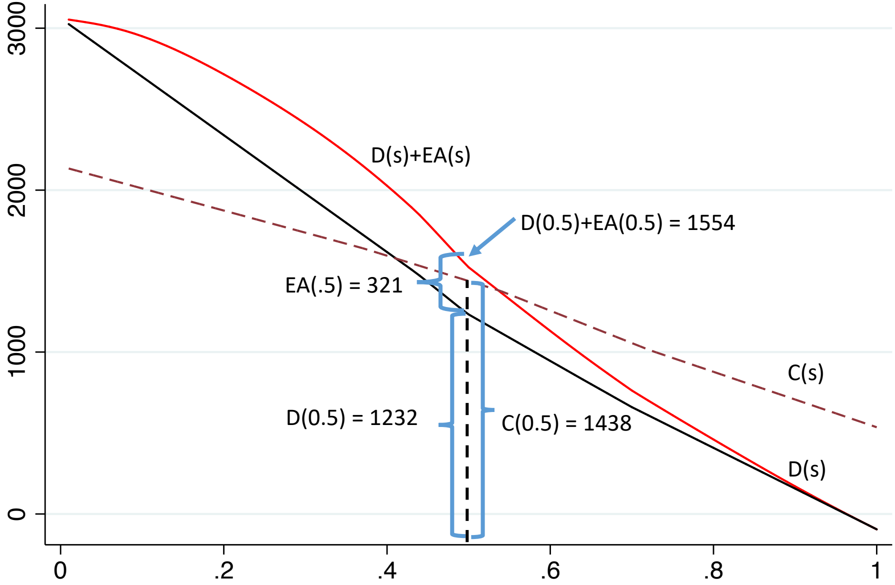




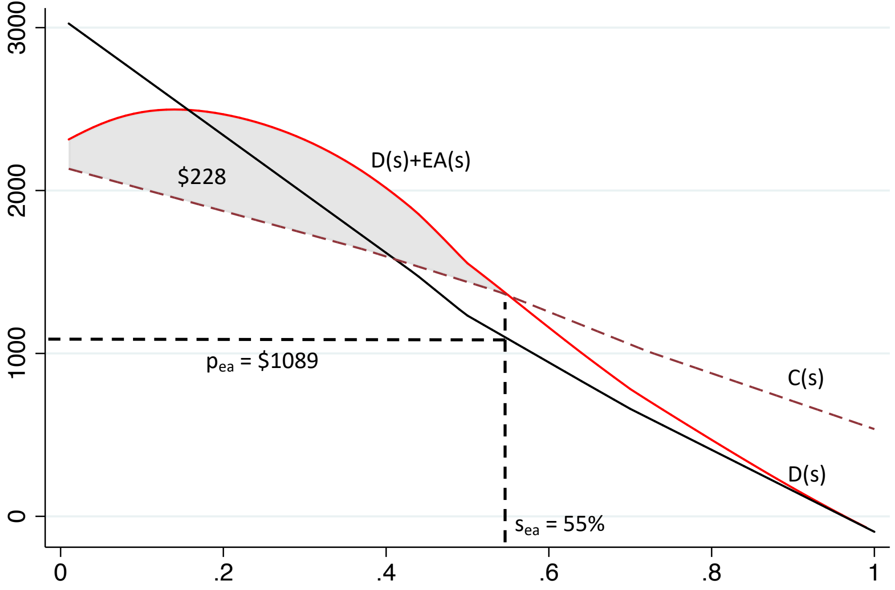
Market Surplus Maximizing Allocation
$ per year
3000
2000
1000
0
$182
p_{ms} =$1581
C(s)
D(s)
s_{ms} = 41%
0
.2
.4
.6
.8
1
Fraction Insured (s)

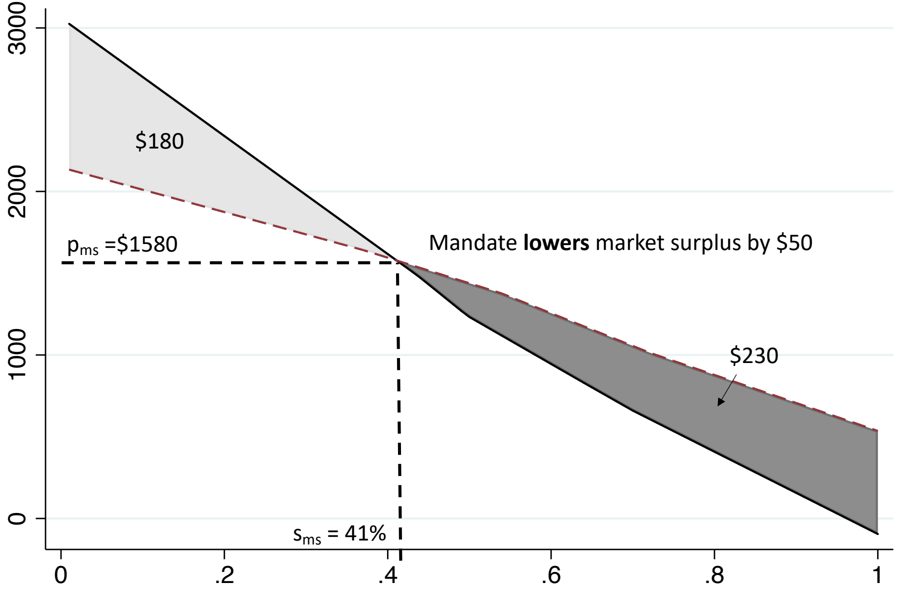
Welfare Cost of Mandates: Market Surplus



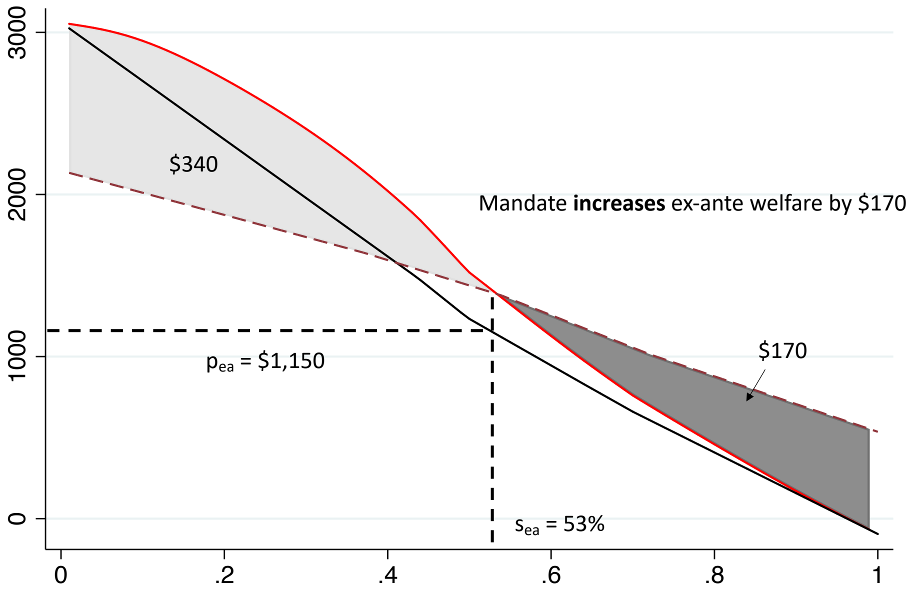


3000
2000
1000
0
0
.2
.4
.6
.8
1
D(s)+EA(s)
D(0.5)+EA(0.5) = 1554
EA(.5) = 321
D(0.5) = 1232
C(0.5) = 1438
C(s)
D(s)


3000
2000
1000
0
0
.2
.4
.6
.8
1
$228
D(s)+EA(s)
p_ea = $1089
C(s)
D(s)
s_ea = 55%



3000
2000
1000
0
$180
p_{ms} =$1580
Mandate **lowers** market surplus by $50
$230
s_{ms} = 41%
0
.2
.4
.6
.8
1



3000
2000
1000
0
0
.2
.4
.6
.8
1
$340
Mandate **increases** ex-ante welfare by $170
p_{ea} = $1,150
$170
s_{ea} = 53%

Summary

- Modest premiums deter coverage substantially and raise costs
  - Adverse selection!
- Low-income WTP for insurance far below cost
  - Consistent with Finkelstein, Hendren, and Luttmer (2016) and fact that uninsured pay 20-30% of their costs
- Contrasts with health insurance for high-income people
  - Consistent with model in which uncompensated care only provided to low-income people
  - Open question: Implications for optimal tax/transfers?!
- Ex-ante welfare perspective can matter in this instance for whether WTP exceeds resource costs

Impacts on Children

- Substantial evidence that public health insurance improves health for children
    - But, contrasts with minimal estimated impacts on adults
- Currie and Gruber (1996, QJE): Health Insurance Eligibility, Utilization of Medical Care, and Child Health
    - Exploits state variation in expansion of Medicaid to children and pregnant mothers

Currie and Gruber (1996)

$$(1) \quad UTIL_i = \alpha + \beta_1 X_i + \beta_2 ELIG_i + \beta_3 \delta_j + \beta_4 \tau_t + \beta_5 AGEG_i \times \delta_j + \beta_6 AGEG_i \times \tau_t + \varepsilon_i,$$

where

$UTIL_i$ is a measure of utilization for individual i,
X is a set of control variables,
$ELIG$ is an indicator of the eligibility of individual i for Medicaid,
δ_j and τ_t are a full set of state and year dummies, respectively,
$AGEG$ is a dummy for being in one of five age groups.

Currie and Gruber (1996): Simulated Instruments

Our strategy, therefore, is to use a "simulated instrument" that varies only with the state's legislative environment and not with its economic or demographic characteristics. In order to construct this instrument, we select a national random sample of 300 children of each age (zero to fourteen), in each year, and calculate the fraction of children in this sample who would be eligible for Medicaid given the rules in each state in that year.[20] This measure can be thought of as a convenient parameterization of legislative differences affecting children in different state, year, and age groups—a natural way to summarize the generosity of state Medicaid policy as it affects each group is in terms of the effect it would have on a given, nationally representative, population.

Currie and Gruber (1996)

TABLE IV
MEDICAID ELIGIBILITY AND THE UTILIZATION OF MEDICAL CARE
LINEAR PROBABILITY MODELS: COEFFICIENTS × 10^2

Dependent var	(1) OLS No visit last year	(2) OLS Visit last 2 weeks	(3) OLS Hospital last year	(4) TSLS No visit last year	(5) TSLS Visit last 2 weeks	(6) TSLS Hospital last year
Medicaid	−2.510	−0.119	0.681	−9.553	4.853	3.960
eligibility	(0.309)	(0.237)	(0.153)	(3.037)	(2.803)	(1.646)
Male	−0.034	0.691	0.763	−0.033	0.691	0.763
	(0.159)	(0.132)	(0.078)	(0.159)	(0.132)	(0.078)
Black	4.149	−3.354	−0.611	4.362	−3.505	−0.710
	(0.260)	(0.195)	(0.123)	(0.276)	(0.212)	(0.133)
Hispanic	1.738	−0.922	0.019	1.978	−1.093	−0.093
	(0.294)	(0.234)	(0.140)	(0.311)	(0.254)	(0.150)
Mom is HS	2.809	−0.613	0.264	3.255	−0.927	0.057
dropout	(0.246)	(0.180)	(0.118)	(0.316)	(0.252)	(0.157)
Mom has some	−3.098	1.177	−0.263	−3.269	1.298	−0.183
college	(0.197)	(0.175)	(0.098)	(0.210)	(0.188)	(0.064)
Dad is HS	3.069	−0.832	−0.216	3.365	−1.041	−0.354
dropout	(0.296)	(0.212)	(0.137)	(0.323)	(0.243)	(0.154)
Dad has some	−2.392	0.672	−0.252	−2.378	0.662	−0.258
college	(0.223)	(0.191)	(0.111)	(0.223)	(0.192)	(0.109)
Child is oldest	−2.540	0.990	−0.049	−2.372	0.872	−0.127
	(0.197)	(0.157)	(0.092)	(0.210)	(0.171)	(0.099)
Number of	1.610	−0.640	−0.234	2.111	−0.936	−0.430
siblings	(0.095)	(0.066)	(0.040)	(0.204)	(0.175)	(0.105)
No male head	−5.243	2.195	0.618	−4.985	2.012	0.498
	(0.395)	(0.315)	(0.196)	(0.410)	(0.332)	(0.204)
Mom is	−0.214	1.434	−0.445	0.027	1.264	−0.556
respondent	(0.569)	(0.541)	(0.349)	(0.579)	(0.549)	(0.352)

TABLE V
MEDICAID ELIGIBILITY AND THE SITE OF CARE
ALL REGRESSIONS RUN AS INSTRUMENTAL VARIABLES
MEDICAID ELIGIBILITY COEFFICIENT AND MEANS ARE × 100

	(1) Doctor's office	(2) ER or hospital outpatient clinic	(3) Other site
Medicaid eligibility	5.073	1.174	−1.217
	(2.479)	(1.117)	(1.100)
Mean of dependent var	8.707	1.666	1.473
Number of obs.	227169	227169	227169

Standard errors are in parentheses. All regressions also include all the variables listed in Table V, as well as an intercept; dummy variables for each state, calendar year, and year of age; season dummies; interactions between calendar year and year of age dummies; and interactions between year of age and state dummies. Eligibility is instrumented using simulated eligibility calculated from the CPS, and matched to individuals by state, year, and age. Standard errors are corrected for heteroskedasticity.

Currie and Gruber (1996)

TABLE VI
EFFECTS OF MEDICAID ELIGIBILITY ON CHILD MORTALITY
DEPENDENT VARIABLE IS DEATHS PER 10,000 CHILDREN

	(1) All causes	(2) Internal causes	(3) External causes
Percent eligible	−1.277	−1.016	−0.261
	(0.482)	(0.359)	(0.363)
Mean of dep var	3.807	1.926	1.881
Number of obs	816	816	816

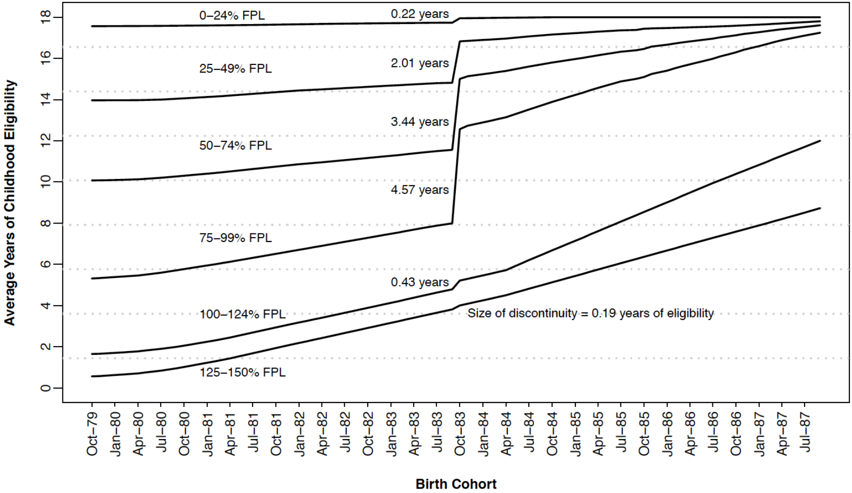
Standard errors are in parenthese. Dependent variable is death rate per 10,000 children in state/year/race/age group, where age groups are 1–4 years old and 5–14 years old. Regressions are run as instrumental variables, where percent eligible in state/year/age group cell is instrumented using simulated eligibility in that cell. Regressions include state, year, and age group dummies. Standard errors are corrected for heteroskedasticity.

Evidence of Medicaid Impacts using Birthdate RD

- Further evidence exploiting Medicaid expansion that offered Medicaid to children born after September 30, 1983
  - Amazing source of identification...
  - Regression discontinuity!
- Wherry, Miller, Kaestner, and Meyer: “Childhood Medicaid Coverage and Later Life Health Outcomes”
- Wherry and Meyer (2015): “Saving Teens: Using a Policy Discontinuity to Estimate the Effects of Medicaid Eligibility”
- Builds on Card and Shore-Sheppard (2004, RESTAT)

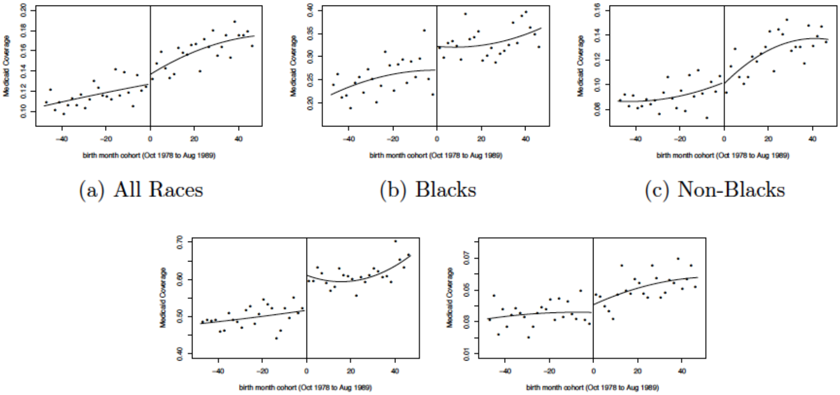
Wherry and Meyer (2015)

Figure 1. Average Years of Childhood Eligibility for Medicaid/SCHIP by Birth Cohort and Family Income (%FPL)



Notes: Weighted average calculated using the characteristics and state of residence of a sample of children of ages 0–17 in the 1981–1988 March CPS. See text for more information. Family income is indexed using the CPI–U and assumed to be constant over the child's lifetime.

Figure 3: Medicaid Coverage in Childhood, Ages 8 to 13, NHIS



(a) All Races

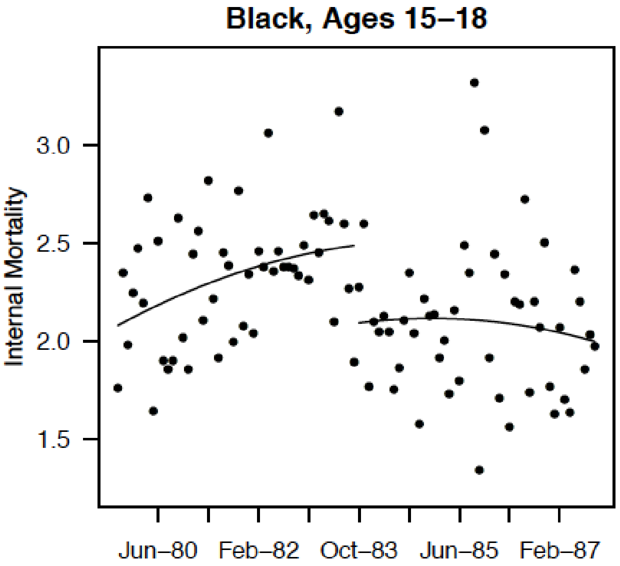
(b) Blacks

(c) Non-Blacks

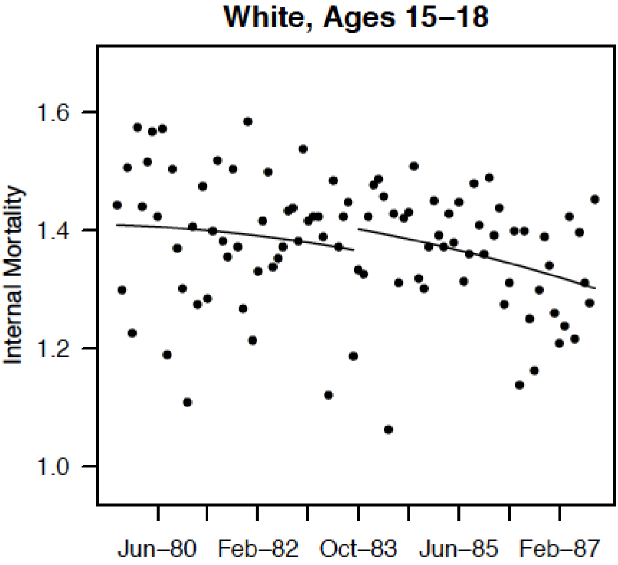
(d) Households below poverty level

(e) Households above poverty level

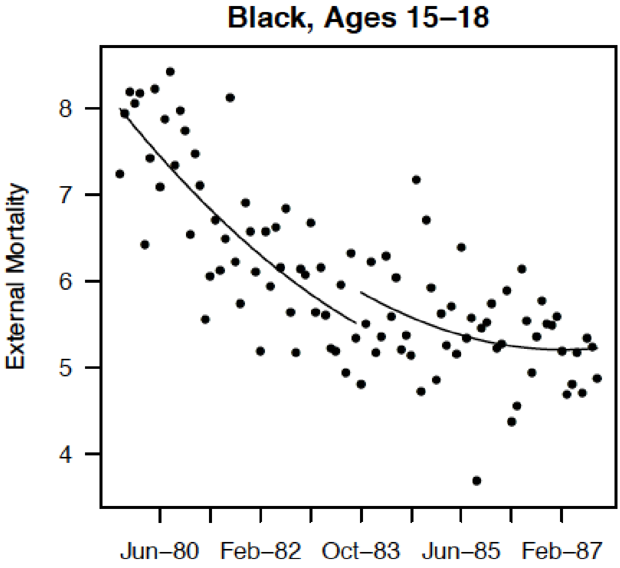
Wherry and Meyer (2015)



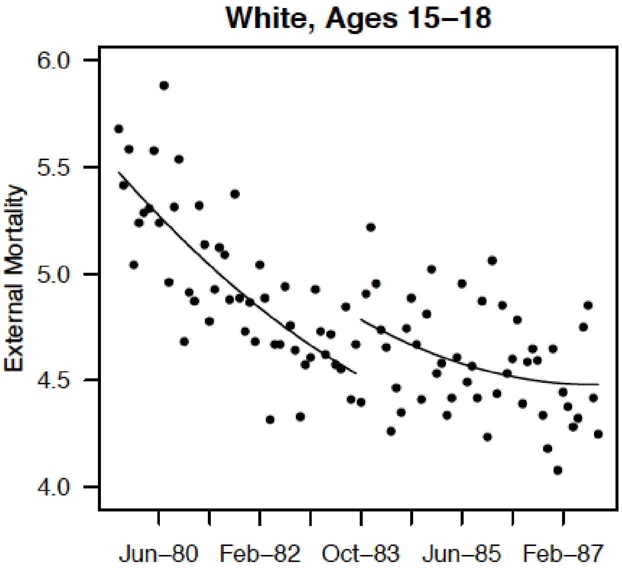
Wherry and Meyer (2015)



Wherry and Meyer (2015)



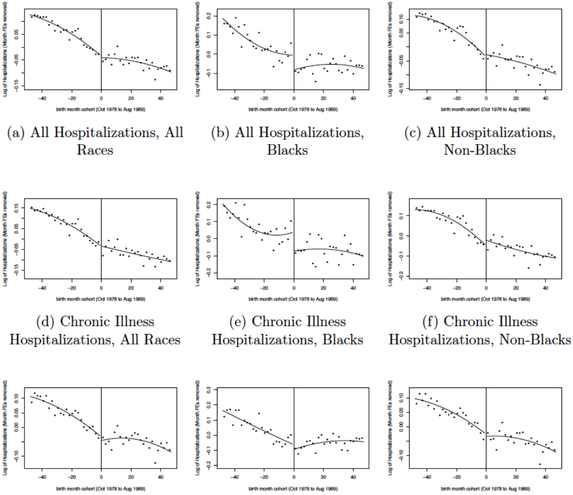
Wherry and Meyer (2015)



Medicaid Impacts on Children

- Evidence Medicaid reduces mortality of children
- What about other health impacts
  - Direct health impacts
  - Impacts on costs later in life
- Wherry, Miller, Kaestner, and Meyer: "Childhood Medicaid Coverage and Later Life Health Outcomes"
  - Look at impacts on later-life hospitalization, ED visits
    - Focus on visits for chronic conditions

Figure 5: 2009 Hospitalizations, Calendar Month of Birth Fixed Effects Removed



(a) All Hospitalizations, All Races

(b) All Hospitalizations, Blacks

(c) All Hospitalizations, Non-Blacks

(d) Chronic Illness Hospitalizations, All Races

(e) Chronic Illness Hospitalizations, Blacks

(f) Chronic Illness Hospitalizations, Non-Blacks

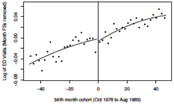
(g) Non-chronic Illness Hospitalizations, All Races

(h) Non-chronic Illness Hospitalizations, Blacks

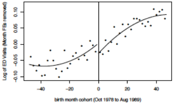
(i) Non-chronic Illness Hospitalizations, Non-Blacks

Wherry and Meyer (2015)

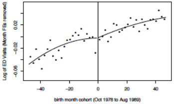
Figure 6: 2009 Emergency Department Visits, Calendar Month of Birth Fixed Effects Removed



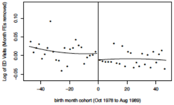
(a) All ED Visits, All Races



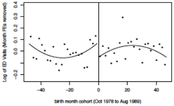
(b) All ED Visits, Blacks



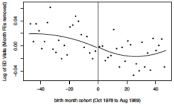
(c) All ED Visits, Non-Blacks



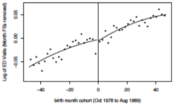
(d) Chronic Illness ED Visits, All Races



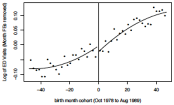
(e) Chronic Illness ED Visits, Blacks



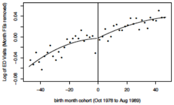
(f) Chronic Illness ED Visits, Non-Blacks



(g) Non-Chronic Illness ED Visits, All Races

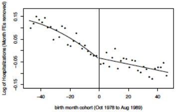


(h) Non-Chronic Illness ED Visits, Blacks

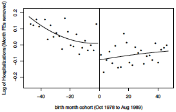


(i) Non-Chronic Illness ED Visits, Non-Blacks

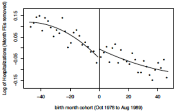
Figure 7: 2009 Hospitalizations, Patients from Low-Income Zipcodes, Calendar Month of Birth Fixed Effects Removed



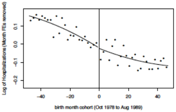
(a) All Hospitalizations, All Races



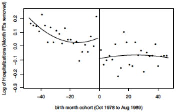
(b) All Hospitalizations, Blacks



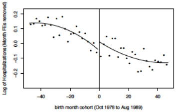
(c) All Hospitalizations, Non-Blacks



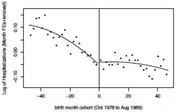
(d) Chronic Illness Hospitalizations, All Races



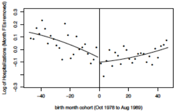
(e) Chronic Illness Hospitalizations in 2009, Blacks



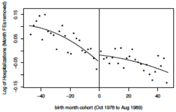
(f) Chronic Illness Hospitalizations in 2009, Non-Blacks



(g) Non-chronic Illness Hospitalizations, All Races



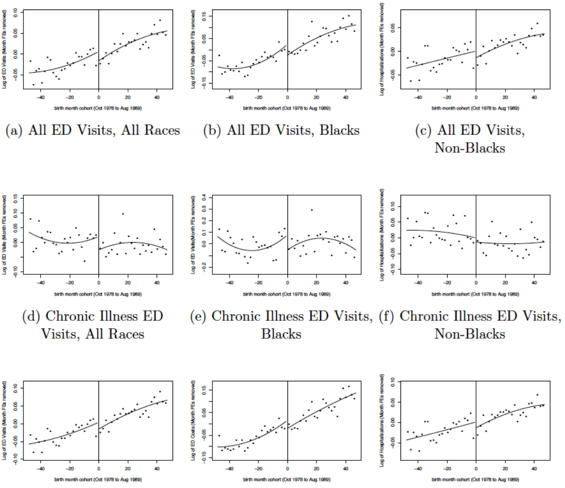
(h) Non-chronic Illness Hospitalizations in 2009, Blacks



(i) Non-chronic Illness Hospitalizations in 2009, Non-Blacks

Wherry and Meyer (2015)

Figure 8: 2009 Emergency Department Visits by Patients from Low-Income Zipcodes, Calendar Month of Birth Fixed Effects Removed

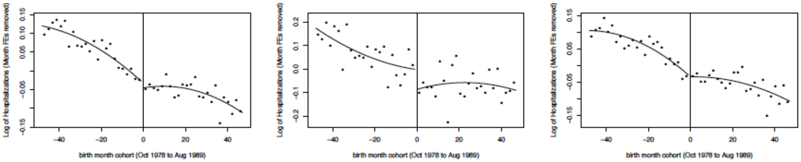


(a) All ED Visits, All Races (b) All ED Visits, Blacks (c) All ED Visits, Non-Blacks

(d) Chronic Illness ED Visits, All Races (e) Chronic Illness ED Visits, Blacks (f) Chronic Illness ED Visits, Non-Blacks

(g) Non-chronic Illness ED Visits, All Races (h) Non-chronic Illness ED Visits, Blacks (i) Non-chronic Illness ED Visits, Non-Blacks

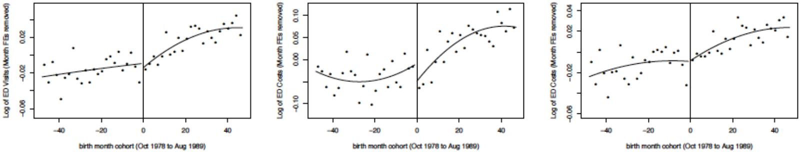
Figure 9: 2009 Hospital Costs, Calendar Month of Birth Fixed Effects Removed



(a) Total Hospital Costs, All Races

(b) Total Hospital Costs, Blacks

(c) Total ED Costs, Non-Blacks



(d) Total ED Costs, All Races

(e) Total ED Costs, Blacks

(f) Total ED Costs, Non-Blacks

Medicaid Impacts on Children

- Medicaid reduced mortality rates
  - Infant mortality (Currie and Gruber 2006)
  - Child mortality (Wherry and Meyer 2015)
- Medicaid reduced later-life chronic conditions and hospitalization
  - Reduced later life costs on the system
  - Reduces cost of medicaid expansion by 2-5%
- But, less impact of Medicaid on adults (e.g. Oregon...)
  - Similar to impact of place via MTO: Significant impacts on children, but not on adults?

Impact of Medicare

- Focus on two papers looking at impact of Medicare
- Exploit:
  - Age 65 discontinuity (Card, Dobkin, and Maestas, 2009)
    - Look at health effects
  - Pre-Medicare variation in coverage rates (Finkelstein, 2007)
    - Look at "GE" effects

Card, Dobkin, and Maestas (2009)

- Card, Dobkin, and Maestas (2009) exploits discontinuity in eligibility for Medicare at age 65
- Document increase in medical care provided
- Document reduction in mortality

Card, Dobkin, and Maestas (2009)

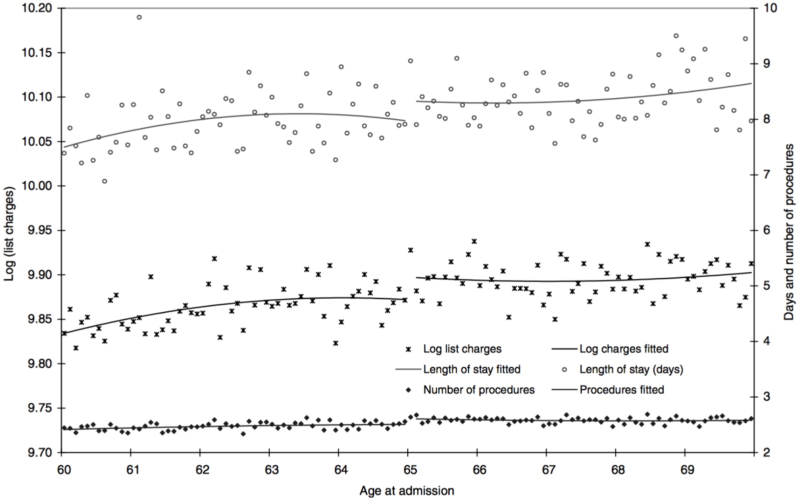


FIGURE V
Three Measures of Inpatient Treatment Intensity

Card, Dobkin, and Maestas (2009)

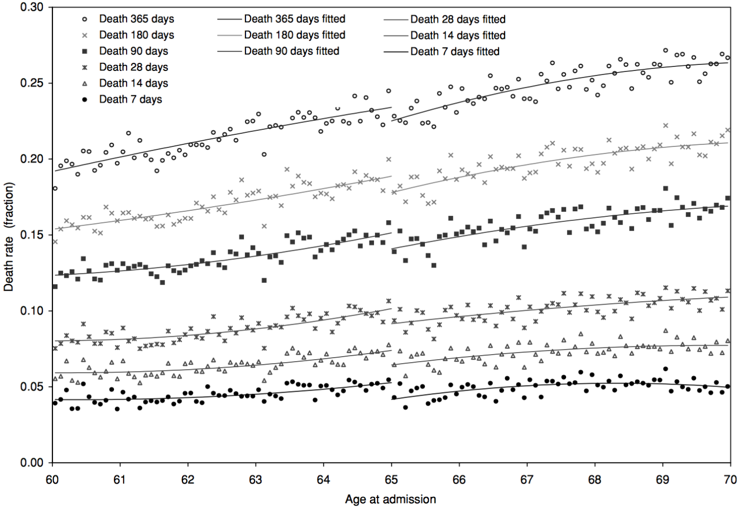


FIGURE VI
Patient Mortality Rates over Different Follow-Up Intervals

GE Effects of Health Insurance: Finkelstein (2007)

- Health insurance can have effects on providers
- Health expenditures are growing dramatically
  - Could health insurance cause this growth?
- Increases incentive to innovate by creating excess demand
  - Is this bad from a welfare perspective?
- Finkelstein (2007): Studies impact of Medicare introduction

Finkelstein (2007): Empirical Strategy

- Empirical analysis of Medicare is difficult
  - Medicare is a national program!
- Enacted in 1965
  - Finkelstein (2007): exploit variation in pre-1965 insurance rates

Finkelstein (2007): Pre-1965 Insurance

TABLE I
SHARE OF ELDERLY WITHOUT HOSPITAL INSURANCE, 1963

	Blue Cross	Any insurance
New England (CT, ME, MA, NH, RI, VT)	0.49	0.37
Middle Atlantic (NJ, NY, PA)	0.60	0.41
East North Central, Eastern Part (MI, OH)	0.55	0.32
East North Central, Western Part (IL, IN, WI)	0.75	0.42
West North Central (IA, KS, MN, MO, NE, ND, SD)	0.81	0.47
South Atlantic, Upper Part (DE, DC, MD, VA, WV)	0.75	0.45
South Atlantic, Lower Part (FL, GA, NC, SC)	0.81	0.50
East South Central (AL, KY, MS, TN)	0.88	0.57
West South Central (AR, LA, OK, TX)	0.85	0.55
Mountain (AZ, CO, ID, MT, NV, NM, UT, WY)	0.78	0.50
Pacific (OR, WA, CA, AK, HI)	0.87	0.52
National Total	0.75	0.45

Data are from individuals aged 65 and over in the 1963 National Health Survey. Sample size is 12,757. Minimum sample size for a subregion is 377.

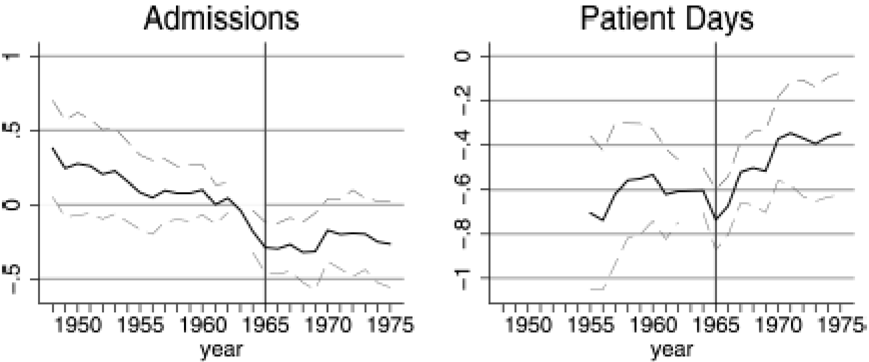
Finkelstein (2007): Estimating Equation

$$log\left(y_{ijt}\right) = \alpha_j + \delta_t + \sum_{t=1948}^{1975} \lambda_t Mcareimpact_z * year_t + X_{st}\beta + \epsilon_{ijt}$$

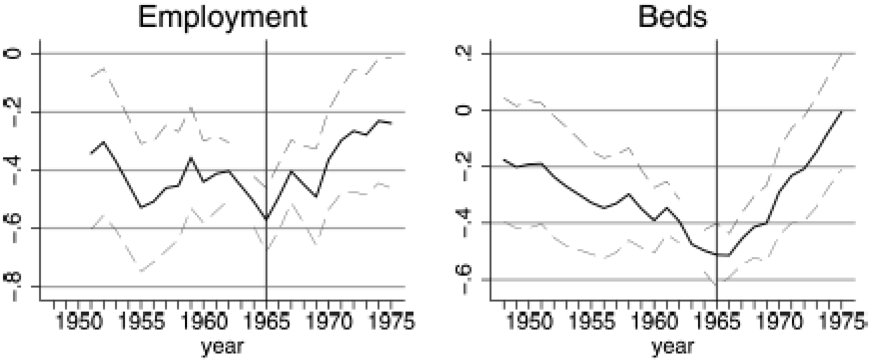
where:

- y_{ijt} is outcome in hospital i in county j at time t
- α_j is county fixed effect
- δ_t is year fixed effect
- X_{st} is outcomes in state s at time t
- $Mcareimpact_z$ = % elderly in region z without Blue Cross hospital insurance in 1963
- Does $\lambda_{post} - \lambda_{pre}$ capture GE effects? What might be missing?

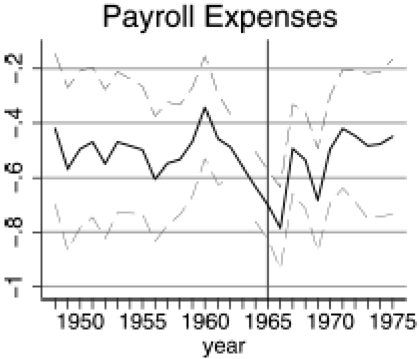
Finkelstein (2007): Main Results

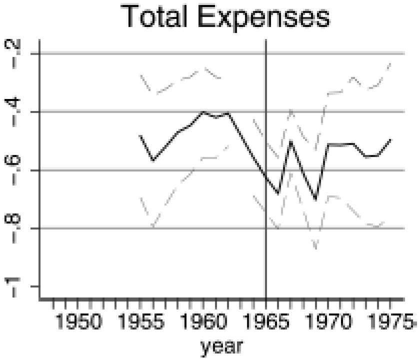


Finkelstein (2007): Main Results



Finkelstein (2007): Main Results





Finkelstein (2007): Entry and Exit

TABLE VI
ANALYSIS OF EXIT AND ENTRY

	Entry analysis (columns 1–2)		Exit analysis (columns 3–4)	
	Unweighted OLS (1)	Weighted OLS (2)	Unweighted OLS (3)	Weighted OLS (4)
$(t - 1965) \times$ Mcareimpact	0.116***	0.121***	0.011	0.013
	(0.019)	(0.017)	(0.011)	(0.010)
Mean dep. var. in 1970	0.18	0.18	0.14	0.17

Table reports the coefficient on $(t - 1965) \times$ Mcareimpact (i.e., β_2) from estimating the OLS deviation-from-trend analysis at the market level (4). For the entry analysis, the dependent variable is the proportion of hospitals in market m in 1960 that have entered between 1960 and year t. For the exit analysis, the dependent variable is the proportion of hospitals in market m in 1960 that have left between 1960 and year t. For all estimates, the sample is limited to 1960 through 1970. All analyses include eight time-varying state-level indicator variables for the number of years before (or since) the implementation of Medicaid in state s. Weighted estimations (in columns 2 and 4) use the number of patient days in a given market in 1960 to weight each market's observations. Standard errors are in parentheses and are calculated allowing for an arbitrary variance–covariance matrix within each hospital market.

***,**, * denotes statistical significance at the 1, 5, and 10 percent levels, respectively. $N = 2{,}832$.

Finkelstein (2007): Adoption of new technologies

- Paper also looks at impact of adoption of new technologies by hospitals:

$$Newtech_{is} = \lambda Mcareimpact_z + X_s\beta + \epsilon_{is}$$

- Newtech indicates adoption of technology in hospital i in state s
  - NOTE: Only cross-sectional data available...
  - Potential bias?

Finkelstein (2007): Results

TABLE VII
MEDICARE AND THE ADOPTION OF NEW CARDIAC TECHNOLOGIES

	Analysis of open heart surgery (columns 1–5)					Analysis of CICU (columns 6–7)		Difference-in-differences analysis (columns 8–9)	
	Open heart surgery facility (1)	EEG (2)	Postop recovery room (3)	Diagnostic radioactive isotope (4)	Intensive care unit (5)	*CICU* (6)	Postoperative recovery room (7)	Open heart surgery vs. controls (8)	CICU vs. postoperative recovery room (9)
Without state-level covariates	*0.0004*	−0.182***	−0.087**	−0.210***	−0.143***	*−0.097*	−0.341***	0.150***	0.243***
	(0.065)	(0.059)	(0.044)	(0.068)	(0.053)	*(0.095)*	(0.106)	(0.046)	(0.077)
With state-level covariates	*0.015*	−0.087	−0.049	−0.118	−0.054	*0.102*	−0.327**	0.123***	0.247***
	(0.063)	(0.063)	(0.057)	(0.072)	(0.062)	*(0.096)*	(0.127)	(0.048)	(0.092)
Year of analysis	*1975*	1950	1951	1955	1958	*1969*	1957		
Mean dependent variable	*0.09*	0.10	0.12	0.10	0.13	*0.35*	0.35		
Estimating equation	*(6)*	(6)	(6)	(6)	(6)	*(6)*	(6)	(7)	(7)

All estimates are marginal effects from probit estimation. Columns (1) through (7) report the marginal effect of Mcareimpact from estimation of (6); dependent variable is shown in column heading and results for cardiac technologies are in italic. Columns (8) and (9) report the marginal effect of the interaction of Mcareimpact with CARDIAC indicator from estimation of (7). CARDIAC is 1 for the cardiac technology in the analysis, (open heart surgery or CICU) and 0 otherwise. Standard errors (in parentheses) are adjusted for correlation within hospital markets. First row reports results from regressions without covariates. Second row reports results from a separate regression which adds controls for state-level socio-economic characteristics (specifically, real per capita state income, state infant mortality rate, violent crime rate, and state population).

Summary

- Public health insurance for adults leads to:
  - Reductions in OOP spending
  - Reductions in financial strain
    - And reductions in uncompensated care
  - But, beneficiaries generally not willing to pay full cost
    - Perhaps because incidence is on third parties
- Public health insurance for children leads to:
  - Reductions in infant and child mortality
  - Reductions in future medical costs and chronic conditions
- Evidence of GE effects of health insurance on hospital entry and new technologies