Policy Evaluation - Quasi-Experimental Research Designs

April 16, 2026

Estimating Treatment Effects Review

- $ATE = Avg_n[Y^1 - Y^0]$
- $ATE_{est} = Avg_n[Y^1|D=1] - Avg_n[Y^0|D=0]$
- When $(Y^1, Y^0) \not\perp\!\!\!\perp D$:

$$ATE_{est} = ATE + \underbrace{\{Avg_n[Y^0|D=1] - Avg_n[Y^0|D=0]\}}_{\text{Selection Bias}} + \underbrace{(1-\pi)(ATT - ATU)}_{\text{Heterogeneous Treatment Effect Bias}}$$

- $ATE_{est} = \beta_0 + \beta_1 D + \beta_2 X_1 + \beta_3 X_2 + ...\beta_k X_{k-1} + \varepsilon$
- Regression with matching
- Natural experiment w/randomization (Oregon): $(Y^1, Y^0) \perp\!\!\!\perp D$

Health Insurance (Medicaid) and Mortality

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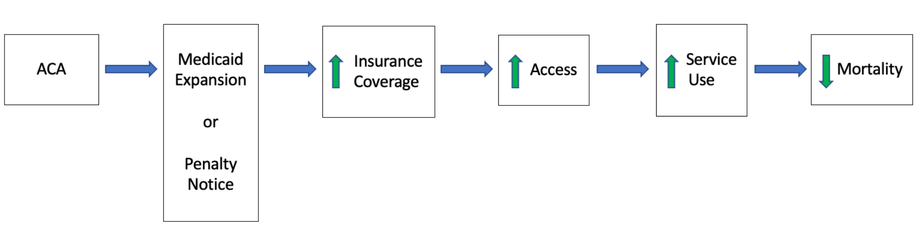

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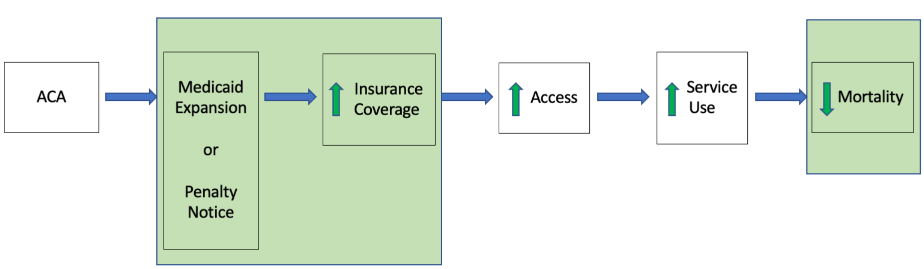

Health Insurance and Mortality - Goldin, Lurie, and McCubbin

Department of the Treasury
Internal Revenue Service

January 12 , 2017

Why am I getting this letter?
The law requires people to have a minimum level of health coverage, qualify for an exemption, or pay a penalty when they file their taxes. Our records show you reported owing this penalty when you filed your 2015 taxes because you or someone in your family did not have health insurance during that year. If you don't have health insurance or an exemption next year, you'll likely owe a penalty for 2017 as well. We are writing to make sure you know how you can avoid this penalty by signing up for health insurance.

How do I avoid the penalty next year?
If you don't have health coverage, you can avoid owing a penalty for most or all of 2017 by signing up for health insurance soon. One way to get insurance is to sign up at HealthCare.gov **before January 31, 2017**. If you already have health coverage, you won't owe a penalty as long as you stay covered.

How much will my penalty be next year if I don't sign up?
The penalty for not having any health coverage in 2017 will be about if your income and family size have not changed since 2015.

How much does health insurance at HealthCare.gov cost?
Most people who enroll in a plan through HealthCare.gov can find plans for **$75 a month or less** after financial help. At HealthCare.gov, you can compare plans to find one that meets your needs and budget.

How do I sign up for health insurance or get help finding a plan?
You can apply online by computer or mobile device, or you can get help in-person or by phone.

- Visit HealthCare.gov, select your state, and follow the step-by-step directions.
- Find in-person help from someone in your community at LocalHelp.HealthCare.gov.
- For questions or help signing up, call

When is the deadline to sign up?
January 31, 2017, is the last day to enroll in a 2017 plan on HealthCare.gov.

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  - Sample period is 2017-2018

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TABLE I

SUMMARY STATISTICS AND BALANCE CHECKS

	Experimental Sample			
	All	Treatment	Control	Difference p-value
	(3)	(4)	(5)	(6)
Individual characteristics				
Female	0.450	0.450	0.451	.679
Age (years)	31.1	31.1	31.1	.410
0–18	0.271	0.271	0.271	.384
19–26	0.136	0.136	0.136	.771
27–44	0.349	0.349	0.349	.684
45–64	0.230	0.230	0.230	.977
65 or older	0.014	0.014	0.014	.506
Household characteristics				
Married	0.414	0.414	0.414	.863
Household income	42,709	42,697	42,782	.346
Income < 138% FPL	0.267	0.267	0.266	.136
Household size	2.74	2.74	2.74	.741
Self-prepared returns	0.341	0.341	0.341	.827
Local characteristics				
High school degree or higher	0.835	0.835	0.835	.553
BA degree or higher	0.249	0.249	0.249	.335
Expansion state	0.560	0.560	0.560	.822
State-based marketplace	0.222	0.222	0.222	.637
Observations				
Individuals	8,893,653	7,647,822	1,245,831	
Households	4,526,717	3,892,847	633,870	

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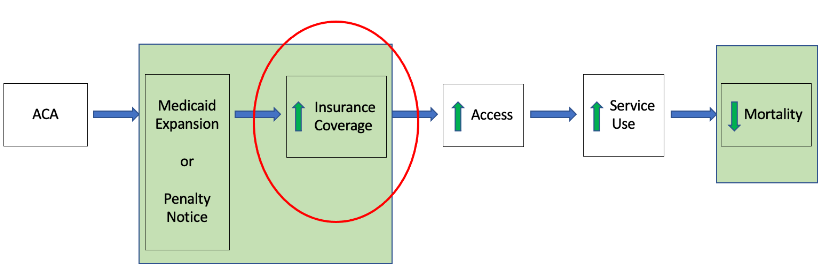
- First estimate coverage effects of taxpayer outreach.



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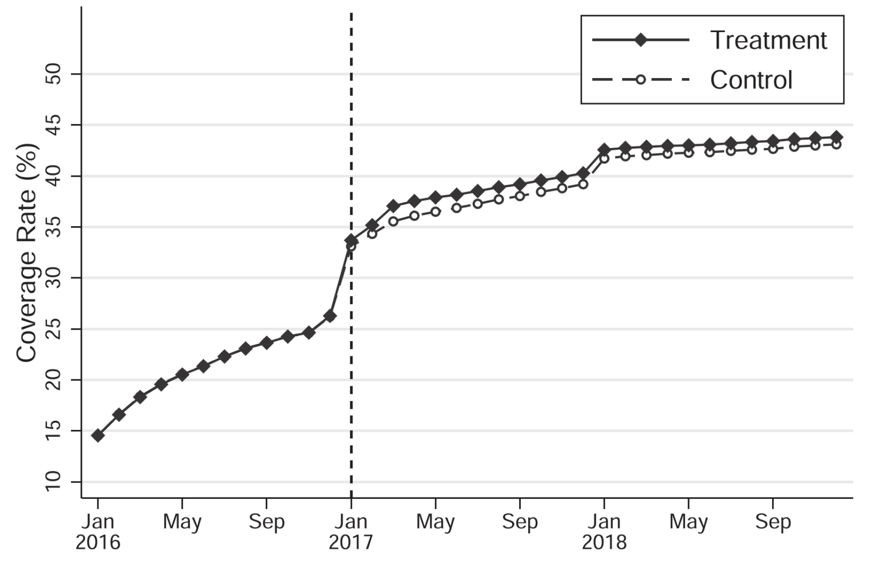
- Health Insurance Coverage



- Health Insurance Coverage

	Prior-year uninsured	
	Months of coverage (5)	At least 1 month of coverage (6)
Panel A: All ages		
Treated	0.232	1.107
	(0.016)	(0.077)
Control mean	9.512	58.525
Observations	5,084,165	5,084,165
Panel B: Middle-aged adults (45 to 64)		
Treated	0.358	1.831
	(0.026)	(0.135)
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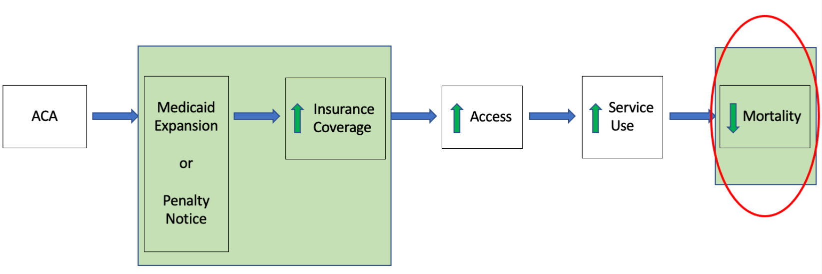
- **Outreach increases probability of at least 1 month of coverage by:**
  - (1.107/58.525)*100 = 1.89%
  - (1.831/48.753)*100 = 3.76%

- Next estimate mortality effects of taxpayer outreach (and insurance coverage).



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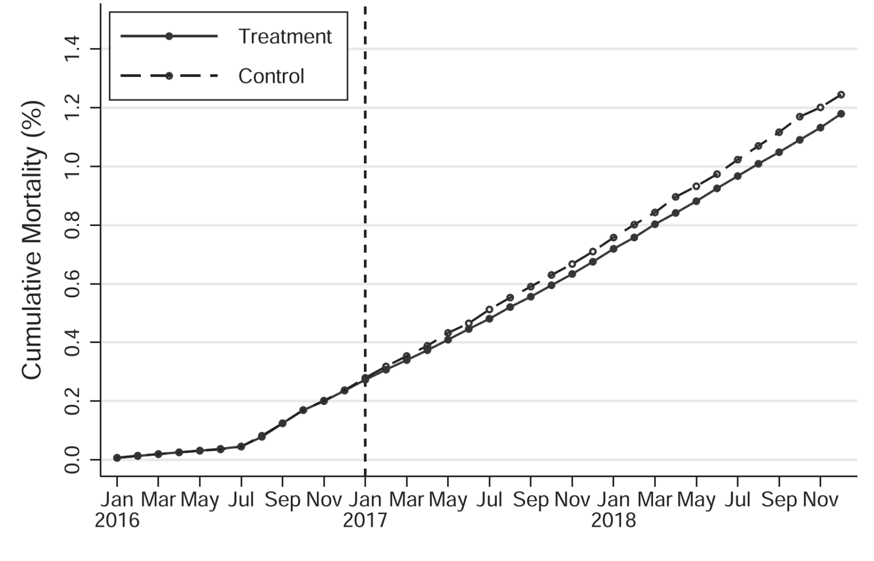

- Mortality

EFFECTS OF INTERVENTION AND COVERAGE ON MIDDLE-AGE MORTALITY

	Mortality (ITT) (1)	Mortality (TOT) (4)
Treated	−0.063	
	(0.025)	
Covered months		−0.178
		(0.070)
Control mean	1.007	1.007
Observations	1,358,983	1,358,983

- ITT = Average difference in mortality between treatment and control groups

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- **Penalty notice decreased mortality by:**
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- Penalty notice decreased mortality by:
  - (-0.063/1.007)*100 = 6.26%
- **Each additional month of coverage decreased mortality by:**
  - (-0.178/1.007)*100 = 17.7%

- ITT = Average difference in mortality between treatment and control groups
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Quasi-Experimental Research Design

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  - ATE $=$ $(E[Y^1_{treat}|Post] - E[Y^0_{treat}|Pre]) - (E[Y^0_{cont}|Post] - E[Y^0_{cont}|Pre])$

Quasi-Experimental Research Design - Difference-in-Differences

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  - Economic theory suggests that higher employment costs will reduce demand for labor
  - April 1, 1992: New Jersey raises minimum wage from \$4.25 to \$5.05 per hour
  - Collected data on employment in 400 fast food restaurants in the Philadelphia area in February 1992 (pre-NJ increase) and again in November 1992 (post-increase).

Quasi-Experimental Research Design - Difference-in-Differences

- Card & Kruegar (1994) - Minimum Wages and Employment

Quasi-Experimental Research Design - Difference-in-Differences

- ATE $= (E[Y^1_{NJ}|Nov] - E[Y^0_{NJ}|Feb]) - (E[Y^0_{PA}|Nov] - E[Y^0_{PA}|Feb])$
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State	Time	Outcome	Diff 1	Diff 2
New Jersey	Pre	$Y = FTE_{NJ}$		
	Post	$Y = FTE_{NJ} + T + D$		
Pennsylvania	Pre	$Y = FTE_{PA}$		
	Post	$Y = FTE_{PA} + T$		

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State	Time	Outcome	Diff 1	Diff 2
New Jersey	Pre	20.4		
	Post	21.0		
Pennsylvania	Pre	23.3		
	Post	21.1		

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New Jersey	Pre	20.4		
	Post	21.0	0.6	
Pennsylvania	Pre	23.3		
	Post	21.1	-2.2	

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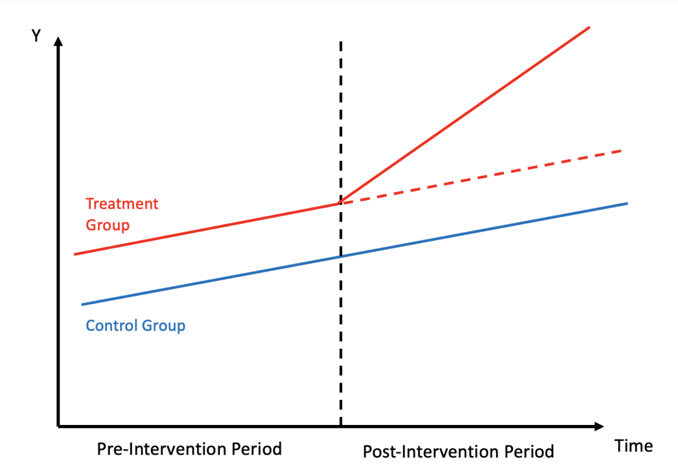
State	Time	Outcome	Diff 1	Diff 2
New Jersey	Pre	20.4		
	Post	21.0	0.6	
				2.8
Pennsylvania	Pre	23.3		
	Post	21.1	-2.2	

Quasi-Experimental Research Design - Difference-in-Differences

- DD Estimating Equation:
  $Y_{st} = \beta_0 + \beta_1 Treat_s + \beta_2 Post_t + \beta_3 Treat_s \times Post_t + \varepsilon_{st}$



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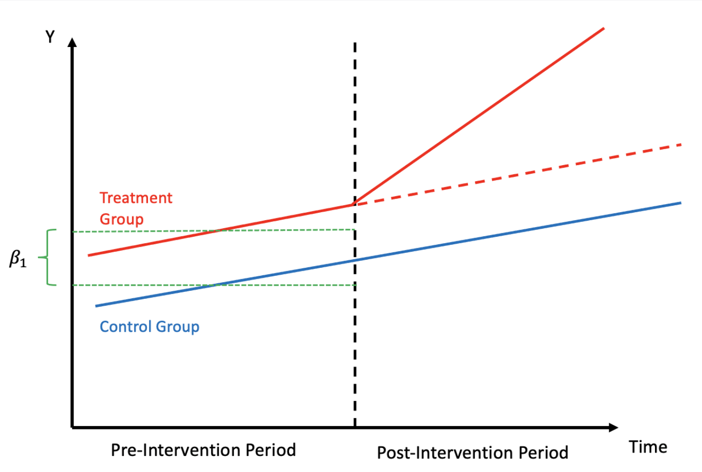

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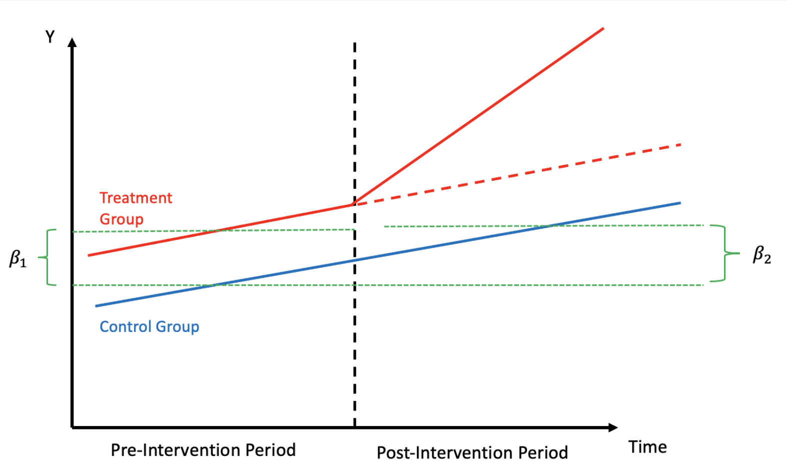

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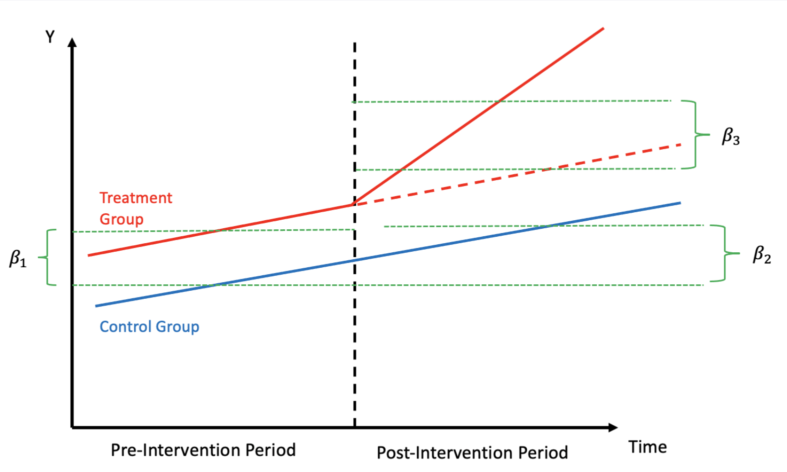

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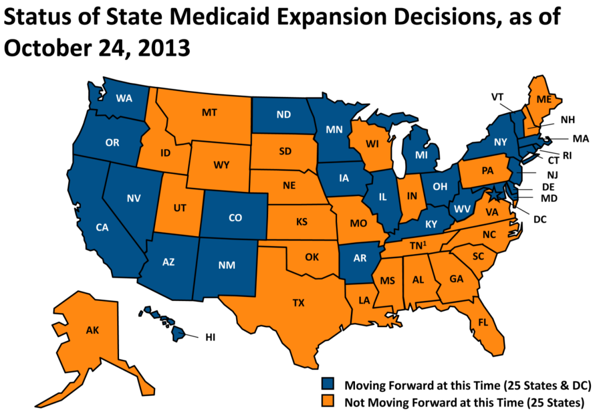
- What ATE are we estimating with DD?
  - Depends. Could be ITT. Could be TOT. Are all units in the treatment group exposed to treatment?

Medicaid and Mortality - Borgschulte and Vogler



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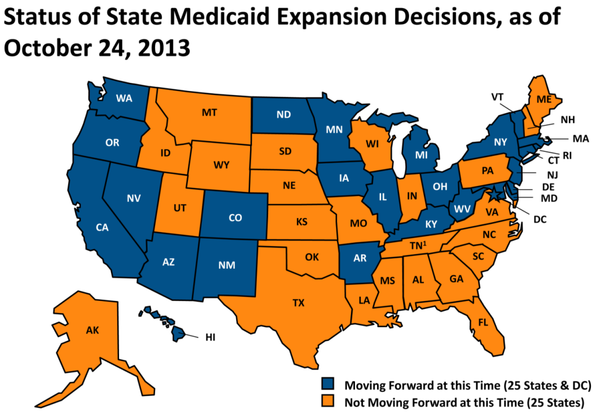

- Estimation Strategy:

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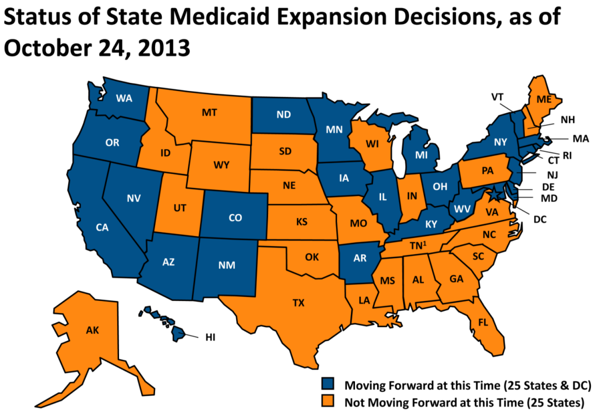

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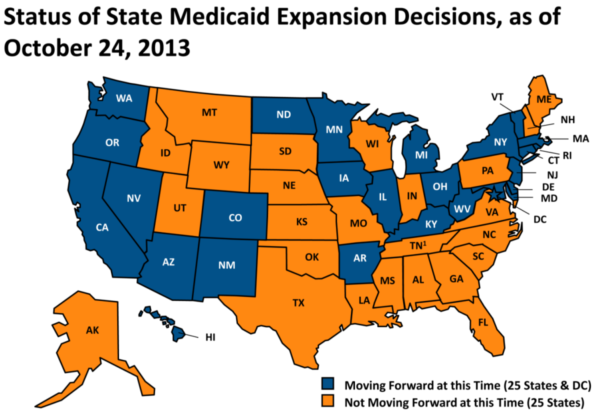

- Estimation Strategy:
  - Difference-in-differences:
    - Expansion vs. non-expansion counties
    - Pre-expansion vs. post-expansion

- Data & Sample:

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  - Data on mortality
    - CDC National Vital Statistics Death Certificate Data
    - Pros: universe of deaths in the U.S. in each year, includes location of residence, includes detailed cause of death
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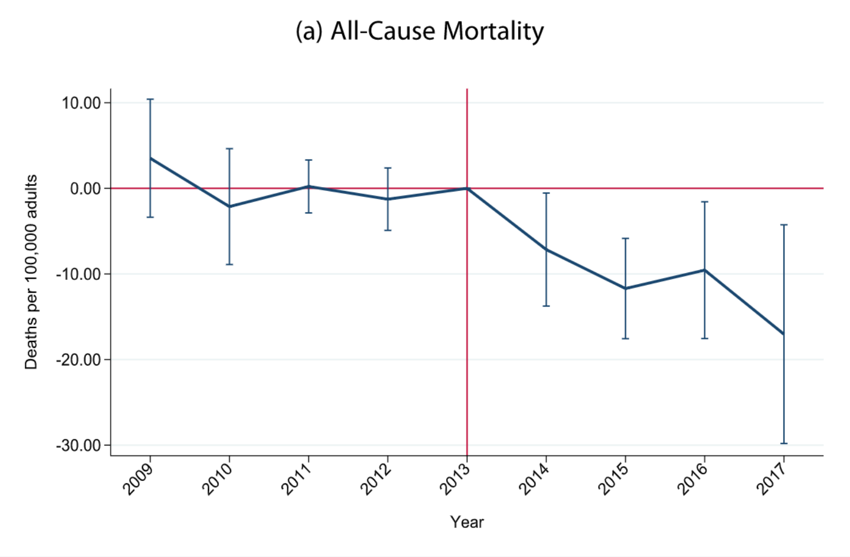
  - Outcome is deaths for those ages 20-64
  - Sample period is from 2009 through 2017
  - Aggregate individual-level data to the county level to create county-level mortality rates (deaths per 100,000 population)

Medicaid and Mortality - Borgschulte and Vogler

- Using the matched county sample:



- Difference-in-Differences Estimates:

Effect of ACA medicaid expansion on mortality.

Model and variable	Full sample	
	Base	Controls
	(1)	(2)
Panel A: All cause mortality		
Medicaid expansion	−14.83**	−11.36***
	(6.12)	(3.59)
% Effect relative to baseline	−4.71	−3.60

Medicaid and Mortality - Borgschulte and Vogler

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- Comparison across studies:
  - Oregon (55 to 64) = 71.7% reduction over 14 months (NS)
  - Goldin et al. (45 to 64) = 17.7% per month of coverage
  - Borgschulte and Vogler (55 to 64) = 30% reduction over 4 years