Appendix for

The Effect of Health Insurance on Mortality: Power Analysis and What We Can Learn from the Affordable Care Act Coverage Expansions

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Abstract

This Appendix contains additional methods details and results for Black, Hollingsworth, Nunes, and Simon, *The Effect of Health Insurance on Mortality: Power Analysis and What Can We Learn from the Affordable Care Act Coverage Expansions?*

A1. Synthetic Control Results

We sought to assess whether we could obtain a better match between treated and control states, and thus tighter confidence bounds, using synthetic control methods. We used two approaches. In the first, we combined the Full-Expansion States into a single treated unit and used usual synthetic control methods (Abadie, Diamond, and Hainmueller, 2010)[1] to construct a synthetic match using the Non-Expansion States as donor states. We report results in Figure A-2, and report the weights on donor states in Table A-12.

The synthetic control approach minimizes the difference between the pre-treatment mortality rates of the treated states and a weighted combination of the Non-Expansion States. However, the maximum difference between the two series is still sizeable, at around 0.02 in 2007. Moreover, visually, a large gap arises in 2013. Thus, this approach fails to create a close enough match in 2013 for this method to produce a satisfying solution to our concern with non-parallel trends. We were not persuaded that, for our data, the synthetic control approach is an improvement over the triple-difference design.[2]

We also considered an extension of the synthetic control strategy, following Xu (2017). Xu's "generalized synthetic control (gsynth)" method generates a separate synthetic control for each full-expansion state, drawn from the non-expansion states. One can then conduct DD analyses on the resulting treated and control units, and obtain analytical standard errors (which the original method does not provide). This procedure does not allow for weighting different units. We therefore only discuss state-level results.[3] While we cannot exactly replicate our triple difference models using the gsynth method, we constructed an approximation, by using as the treated units each treated state's 55 to 64 year olds, and as the donor pool both every non-expansion state's 55 to 64 year olds and every state's (expansion or not) 65 to 74 year olds. We present results in Appendix Figure A-3. Similar to the simpler synthetic control method presented above, there is a large drop in amenable mortality in Full-Expansion States in 2013; mortality in expansion states then rebounds in 2014. The poor pre-period fit is even more pronounced with county-level data, and is driven by small counties, which have highly varying death

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[1] We used code for this approach from Soni (2016).

[2] A further concern with the synthetic control approach is that it gives zero weight to most donor states and assigns positive weights to several very-low-population states (Alaska, Maine, Wyoming) that do not otherwise seem good matches for the Full-Expansion States. Appendix Table A-8 shows the weights on each donor state.

[3] Although we could not directly use population weights within Xu's method, we simulate doing so by repeatedly running his procedure on bootstrapped datasets with draws weighted by population. Results, with both state-level and county-level data, were similar to those we discuss in the text.

rates and are hard to fit even with a large donor pool. We concluded that the gsynth approach cannot be reliably applied to our data

A2. Results for Different Demographic Groups

In this and the next two sections, we assess the effects of Medicaid expansion on mortality for various subgroups. The demographic groups we consider are males, females, non-Hispanic blacks, non-Hispanic whites, and Hispanics. We also consider subgroups based on education and mortality based on cause of death. Our data has limitations for all subgroups except gender. For race and ethnicity, we can obtain estimates of the first stage (change in uninsurance rates) only at the state level, not the county level, due to limitations of the SAHIE data. The DD design does not explicitly use the first stage, but it is central to assessing what coefficient magnitudes are reasonable. For education, population data is available only for broad age groups (45-64 and 65+; 5-year average). For analysis by prior insurance status and by income, we observe percent uninsured and percent below 138% of the FPL threshold for full ACA expansion at the county*year level, but cannot directly study these subsamples because the mortality data does not contain information on income or insurance.

We begin our analysis of demographic subgroups in Figure A-5 with leads-and-lags graphs of the triple differences in amenable mortality for samples subdivided on gender and on race/ethnicity. Most post-expansion point estimates are insignificant. The exception is non-Hispanic Blacks, who show a post-expansion drop in mortality. However, for this subgroup, we observe non-parallel pre-treatment trends even with the triple-difference specification; the post-expansion drop in mortality could merely reflect continuation of those trends. Also, the first stage for non-Hispanic Blacks is not greatly different from that for the population as a whole (Table A-3). Thus, the point estimates in Figure A-5 (around -0.05) are not possible as true effects of Medicaid expansion.

We turn next to DD and triple-difference regression results for amenable mortality for these subsamples, starting with demographic subsamples in Table A-3. The "all" row in Table A-3 is the same as in text Table 2. The first column of Table A-3 shows the first-stage change in uninsurance rates for Full- versus Non-Expansion States, in percent, for persons aged 50-64 (the closest available age match to our main treatment sample). All first stages are small; the largest is for Hispanics at 1.5% (not significant).

In Table A-3, a number of the DD coefficients in column (2) are significant and negative, but significance disappears in the triple-difference specification except for non-Hispanic Blacks. However, as noted above, these estimates are suspect due to non-parallel pre-treatment trends and implausibly large point estimates. We are also wary of assigning too much importance to statistically significant results in particular specifications given the number of estimates we produced, although we did not conduct formal Bonferroni type p-value adjustments.

A3 Variation Based on Education Level

In Figure A-6, we show leads-and-lags graphs for the triple difference in amenable mortality for subsamples stratified on education. Low education predicts poverty and hence eligibility for Medicaid expansion; it may also affect the mortality response to the "treatment" of obtaining Medicaid. Recall that for these subsamples, we study persons aged 45-64, and the triple difference compares these persons to all persons age 65+. We present leads-and-lags graphs for elementary school only; partial high school without graduating; high-school graduate; and some college. There is no evidence of a post-expansion decline in mortality for any subgroup, including the less-than-high-school groups.

In Table A-4, we show regression results by education level. The first row shows full sample results. These differ from text Table 2 due to the broader age range that we use due to data limitations. Note that in our preferred triple-difference specification, the point estimate for overall mortality is now positive (higher mortality) and insignificant, and that Medicaid expansion predicts a significant drop in mortality for the elderly (a placebo group). Both results cast further doubt on whether an effect of Medicaid expansion on mortality can be reliably detected.

The first column shows the relevant first stages. The first stage is close to 4% for persons without a high school degree, but drops to 1.5% for high school graduates with no college, and to 1% for persons with some college**.** However, the non-high-school graduates are only 12% of the 45-64 age group, so the power gained from a stronger first stage is offset by smaller sample size.

The first row shows full sample results. The second through fifth rows show effects for the four education groups, starting with the lowest group, those with only elementary school completion, while the other rows show successively higher education categories. All DD and triple-difference point estimates are insignificant, consistent with the leads-and-lags graphs in Figure 5. The point estimate for three of the four education groups, including the least educated, are positive (opposite from predicted).

A4. Variation by Primary Cause of Death

In Table A-5, we present results by cause of death, for the top 4 causes of death: cancer, diabetes, cardiovascular causes, and respiratory illnesses, and also for HIV. Figure A-7 provides the corresponding leads-and-lags graphs. All of these causes are within the broad category of amenable mortality. First-stage estimates are not available with our data, because we lack data on Medicaid insurance takeup among those with specific diseases. However, Soni et al. (2018a, 2018b) use a DiD design based on Medicaid expansion and report a 2.4% first stage among persons with cancer diagnoses and a 6.4% increase in early-stage cancer diagnoses. Diabetics could plausibly benefit more strongly from Medicaid expansion given the negative correlation between income and diabetes prevalence and evidence from the Oregon Medicaid Experiment that gaining Medicaid insurance predicts increased diabetes diagnosis (Baicker et al., 2013). HIV is another specific condition, for which health insurance has predicted lower mortality in previous studies (Goldman et al., 2001). However, both DD and triple-difference coefficients are insignificant for all causes of death.

A5. Variation by Pre-ACA Uninsurance and Poverty Rates

We turn next to an effort to exploit pre-AC`A uninsurance rates and poverty levels. We cannot measure the second stage (mortality by individual income and insurance status) from the mortality data, so we address this source of heterogeneity indirectly at the county level. The DD specification is the same as above; the third difference for is high-versus-low pre-ACA uninsurance rates in counties. We compare "treated" high-uninsurance counties (the counties with the highest pre-ACA uninsurance rates, defined so that they together contain 20% of the U.S. population) to "control" counties with the lowest pre-ACA uninsurance rates, also containing 20% of the U.S. population; we drop all other counties. This is similar to the analysis in Finkelstein and McKnight (2008), exploiting pre-Medicare variation in insurance levels, and Courtemanche et al. (2017) for the ACA. The third difference for high-vs-low poverty counties is similar: high-poverty counties (the counties with the highest poverty rates, together containing 20% of the US. population) versus low-poverty counties (counties with the lowest poverty rates, also containing 20% of the U.S. population); we drop all other counties. These comparisons rely on all ACA-induced sources of health insurance expansion, rather than Medicaid expansion alone.

We present leads-and-lags graphs for amenable mortality in Figure A-8. Neither graph shows evidence of a treatment effect. Both graphs show signs of a pre-treatment trend toward lower mortality in the last few years prior to ACA expansion, in both high-uninsurance counties and high-poverty counties, which does *not* continue in the post-expansion period and indeed reverses for the high-uninsurance counties.

We present regression estimates in Table A-6, for the full sample and for demographic subsamples. Data are sufficient to let us compute first-stage estimates only for the full sample and for male and female subsamples. The first stage remain quite small. There is no evidence of significant effects of Medicaid expansion on mortality. For the full sample, the coefficients for both subsamples are insignificant. For the comparison of high-vs-low uninsurance counties, the coefficient is positive (opposite from predicted). For the demographic subsamples, five of the 14 coefficients are positive; and the only significant coefficient is also positive.[4]

A6. Alternative Specifications: ATT Weights; All-Non-Elderly Adults; and Total Mortality

In Tables A-7 through A-11, we present results using a number of different specifications. Table A-7 is similar to text Table 2, but uses the following alternative specifications: (i) ATT * population weights (we use population weights in the text); (ii) using linear state trends; (iii) running regressions at the state instead of the county level, with population weights); and running state-level regressions without population weights. All triple-difference coefficients are insignificant. Figure A-9 provides leads-and-lags graphs for amenable mortality with ATT * population weights.

To generate the ATT (average treatment effect on the treated) weights, we first average the covariates over the pre-treatment period (2009-2013). We then run a logit regression, which predicts whether a county is in a Full- or Non-Expansion State, using all variables in Table A-2 to generate the fitted propensities p for each county. ATT weights are calculated as (p/(1-p)).

Figure A-10 presents leads-and-lags graphs for DD and triple differences for total mortality, instead of amenable mortality. Figure A-10 presents leads-and-lags graphs for DD and triple differences for non-amenable mortality.

In Table A-8, we present triple-difference results using these same alternative specifications with each of the demographic subgroups. The significant, negative coefficient for non-Hispanic Blacks survives in several of these specifications, but loses significance in state-level regressions without population weights. All other coefficients are insignificant, except that we find a significant negative coefficient for men in state-level regressions without population weights. The sizeable differences, for several subgroups, between state-level regressions with and without population weights confirm our initial concern that results from this specification are sensitive to outlier results in a few low-population states. Figure A-12 provides leads-and-lags graphs for amenable mortality for demographic subgroups, with ATT * population weights.

In Table A-9, we present triple-difference results with these alternative specifications with each of the education subgroups. All estimated effects are statistically insignificant. Figure A-13

[4] In Table A-6, we use all counties and estimate continuous versions of the comparisons in Table 6 between high and low uninsurance (or poverty) counties, again with insignificant results.

provides leads-and-lags graphs for amenable mortality for education subgroups, with ATT * population weights.

In Table A-10, we present triple-difference results with these alternative specifications with each cause of death. All estimated effects are statistically insignificant. Figure A-14 provides leads-and-lags graphs for amenable mortality by cause of death, with ATT * population weights.

Figure A-15 presents leads-and-lags graphs for the comparison of high-versus low poverty and high-versus low-uninsurance counties, with ATT * population weights. Figure A-16 is similar, but the sample is all non-elderly adults.

In Table A-11, we present triple-difference results using two alternative specifications (ATT * population weights, and comparing all non-elderly adults to all elderly adults), for each of the demographic subgroups. There are some scattered significant coefficients, positive for women and negative for men (with ATT * population weights) and for non-Hispanic Blacks (for the broad age range), but no consistent results across specifications. Figure A-17 presents leads-and-lags graphs for the comparison of amenable mortality for all non-elderly adults.

Across all tables, the scattered significant coefficients that we find are far too large in magnitude to be true causal effects. Indeed, given our standard errors, only implausibly large coefficients would appear to be statistically significant.

Table A-1. Medicaid Expansion States (2014-2016)

This table includes Medicaid expansions through 2016. It is based on combining and reconciling the classification of states as "full expansion," "None," or in-between ("mild" or "substantial" expansion), by Simon, Cawley and Soni (2017), Lou et al. (2018), and Kaiser Family Foundation (2015). Most states could be classified based on their rules for when and to what level they expanded Medicaid for all adults. Arizona required special care; see detailed analysis below. Because our mortality data are annual, we consider New Hampshire to be a 2015 expansion, Alaska to be a 2016 expansion, and Louisiana to be a 2017 expansion, hence beyond our study period.

In the "expansion details" column, "ACA Expansion" means regular expansion to 138% of FPL, on the date stated in the "Effective Date" column. In the "inclusion/exclusion column, C = control (non-expansion), T = treatment (full expansion); other states are excluded. Simon et al. (2017) classify early expansion states as "mild" or "substantial" expansion, based on their assessment of the extent to which enrollment increase with full Affordable Care Act expansion in 2014. This classification of states based on expansion status is also used in Black et al. (2018) ("BHNS"). % change in uninsured enrollees (2013-20156) come from SAHIE estimates for ages 18-64 and considering all income groups.

State	Abbr.	Expansion Details	Effective Date	% change in uninsured enrollees (2013-2016)	Inclusion/ Exclusion	Expansion type	Compare to BHNS
Alabama	AL	None		6.4	C [.]	None	Consistent
Alaska	AK	Medicaid Expansion	09/01/2015	6.8	T [2016]	None	Consistent for 2014-2015 (expanded late 2015)
Arizona[5]	AZ	§ 1115 Waiver (100% FPL, but closed to new enrollees in 2011) ACA Expansion	2000 01/01/2014	9.6	T[2014]	Full	Consistent
Arkansas[6]	AR	§ 1115 Waiver	01/01/2014	12.4	T [2014] Private Option	Full	Consistent
California[7]	CA	§ 1115 Waiver (LA county) § 1115 Waiver (200% FPL) ACA Expansion	01/01/1995 11/01/2010 01/01/2014	13.5	Excluded (Early expansion)	Substantial	Consistent
Colorado[8]	CO	§ 1115 Waiver (to 10% of FPL)	04/01/2012	8.6	T [2016]	Full	Consistent

[5] Arizona used a § 1115 waiver to expand Medicaid coverage to childless adults up to 100% FPL during 2000-2011. In 2011, the state started to phase out that program (transitioning into Medicaid expansion). Which category Arizona belongs in was unclear based on its rules, so we also examined the extent to which Medicaid enrollment increased in 2014. See details below.

[6] Arkansas operated a limited-benefit premium-assistance program for childless adults who worked for small uninsured employers (ARHealthNetworks waiver) prior to the ACA. Arkansas's Medicaid expansion includes a "private option" under which Medicaid-eligible persons receive health insurance from the state insurance exchange, with a small monthly premium.

[7] California expanded Medicaid in 2010-2011, in selected counties.

State	Abbr.	Expansion Details	Effective Date	% change in uninsured enrollees (2013-2016)	Inclusion/ Exclusion	Expansion type	Compare to BHNS
		ACA Expansion	01/01/2014		T [2014]		
Connecticut[9]	CT	State Plan Amendment (56% FPL) ACA Expansion	04/01/2010 01/01/2014	6.4	Excluded (Early Expansion)	Substantial	Consistent
Delaware[10]	DE	ACA Expansion	01/01/1996 01/01/2014	5.1	Excluded (Early Expansion)	Mild	Consistent
District of Columbia[11]	DC	State Plan Amendment (133% FPL) § 1115 Waiver ACA Expansion	07/01/2010 12/01/2010 01/01/2014	4.2	Excluded (Early expansion)	Mild	Consistent
Florida	FL	None		10.4	C [.]	None	Consistent
Georgia	GA	None		7.6	C [.]	None	Consistent
Hawaii[12]	HI	ACA Expansion	08/01/1994 01/01/2014	4.6	Excluded (Early expansion)	Substantial	Consistent
Idaho	ID	None		8.2	C [.]	None	Consistent
Illinois	IL	ACA Expansion	01/01/2014	9.2	T [2014]	Full	Consistent
Indiana	IN	§ 1115 Waiver	02/01/2015	8.5	T [2015]	Full	Consistent
Iowa[13]	IA	§ 1115 Waiver	01/01/2014	5.8	T [2014]	Full	Consistent
Kansas	KS	None		5.2	C [.]	None	Consistent
Kentucky	KY	ACA Expansion	01/01/2014	13.7	T [2014]	Full	Consistent
Louisiana	LA	ACA Expansion	07/01/2016	9.0	C [.]	None	Consistent
Maine	ME	None		4.2	C [.]	None	Consistent
Maryland	MD	ACA Expansion	01/01/2014	5.8	T [2014]	Full	Consistent

[9] Connecticut, elected to enact the Medicaid expansion in 2010 through a state amended plan at 56%. Connecticut expanded its Medicaid program fully in 2014.

[10] In Delaware, childless adults with incomes up to 100% FPL were eligible for Medicaid through the Diamond State Health Plan waiver, effective on 01/01/1996.

[11] DC expanded its Medicaid program at 133% of FPL in 2010.

[12] In Hawaii, childless adults with incomes up to 100% FPL were eligible for the state's QUEST Medicaid managed care waiver program, effective on 08/01/1994.

[13] Under the IowaCare program, childless adults with income below 200% FPL were eligible for health insurance since 2005. However, IowaCare provided limited services in a limited network, so low-income adults in Iowa received a substantial coverage expansion in 2014 (Damiano et al., 2013). During 2014-2015, Iowa residents with income < 100% of FPL were enrolled in Medicaid managed care plans, while those with income of 100-138% of FPL received private insurance obtained through the Iowa health exchange, with premiums waived (a partial "private option"). See https://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Waivers/1115/downloads/ia/Market-Place-Choice-Plan/ia-marketplace-choice-plan-state-term-app-06012016.pdf...

State	Abbr.	Expansion Details	Effective Date	% change in uninsured enrollees (2013-2016)	Inclusion/ Exclusion	Expansion type	Compare to BHNS
Massachusetts[14]	MA	"Romneycare" ACA Expansion	04/12/2006 01/01/2014	1.7	Excluded	Mild	Consistent
Michigan	MI	ACA Expansion	04/01/2014	8.5	T [2014]	Full	Consistent
Minnesota[15]	MN	State Plan Amendment (75% FPL) § 1115 Waiver (200% FPL) ACA Expansion	03/01/2010 08/01/2010 01/01/2014	5.6	Excluded (Early Expansion)	Substantial	Consistent
Mississippi	MS	None		7.3	C [.]	None	Consistent
Missouri	MO	§ 1115 Waiver (St. Louis County Only) (200% FPL) None	07/01/2012	5.7	C [.]	None	Consistent
Montana	MT	ACA Expansion	01/01/2016	11.5	T [2016]	None	Consistent for 2014-2015 (expanded in 2016)
Nebraska	NE	None		4.1	C [.]	None	Consistent
Nevada	NV	ACA Expansion	01/01/2014	11.2	T [2014]	Full	Consistent
New Hampshire[16]	NH	§ 1115 Waiver	08/15/2014	7.0	T [2015]	Full	Consistent
New Jersey[17]	NJ	§ 1115 Waiver (23% FPL) ACA Expansion	04/01/2011 01/01/2014	7.4	T [2014]	Full	Consistent
New Mexico	NM	ACA Expansion	01/01/2014	13.8	T [2014]	Full	Consistent
New York[18]	NY	§ 1115 waiver ACA Expansion	10/01/2001 01/01/2014	6.7	Excluded (Early expansion)	Mild	Consistent
North Carolina	NC	None		7.4	C [.]	None	Consistent

[14] Massachusetts implemented reforms to expand insurance coverage to low-income adults in 2006.

[15] Minnesota conducted early expansion in 2010 two ways. Persons with income $\leq$ 75%FPL were insured through Medical Assistance Medicaid, funded through a State Plan Amendment, persons with income from 75~200% of FPL were insured through MinnesotaCare, funded through a § 1115 Waiver, which had limited benefits and cost-sharing.

[16] New Hampshire implemented a "private option" (mandatory purchase of subsidized private insurance, instead traditional Medicaid, in 2016. See https://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Waivers/1115/downloads/nh/health-protection-program/nh-health-protection-program-premium-assistance-appvl-amend-req-06232015.pdf.

[17] New Jersey's expansion in 2011 only extended to 23% FPL; we therefore treated it as a full expansion state.

[18] In New York, childless adults up to 78% FPL were eligible for the Medicaid (Home Relief) waiver program and childless adults up to 100% FPL were eligible for the Family Health Plus waiver program (Heberlein et al., 2011).

State	Abbr.	Expansion Details	Effective Date	% change in uninsured enrollees (2013-2016)	Inclusion/ Exclusion	Expansion type	Compare to BHNS
North Dakota	ND	ACA Expansion	01/01/2014	6.0	T [2014]	Full	Consistent
Ohio	OH	ACA Expansion	01/01/2014	8.1	T [2014]	Full	Consistent
Oklahoma	OK	None		5.3	C [.]	None	Consistent
Oregon	OR[19]	ACA Expansion	01/01/2014	12.2	T [2014]	Full	Consistent
Pennsylvania	PA	ACA Expansion	01/01/2015	6.2	T [2015]	Full	Consistent
Rhode Island	RI	ACA Expansion	01/01/2014	10.5	T [2014]	Full	Consistent
South Carolina	SC	None		8.1	C [.]	None	Consistent
South Dakota	SD	None		2.9	C [.]	None	Consistent
Tennessee	TN	None		6.8	C [.]	None	Consistent
Texas	TX	None		7.5	C [.]	None	Consistent
Utah	UT	None		6.9	C [.]	None	Consistent
Vermont	VT[20]	§ 1115 Waiver ACA Expansion	01/01/1996 01/01/2014	4.7	Excluded (Early expansion)	Mild	Consistent
Virginia	VA	None		5.3	C [.]	None	Consistent
Washington[21]	WA	§ 1115 Waiver (133% FPL) ACA Expansion	01/03/2011 01/01/2014	11.1	T [2014]	Full	Consistent
West Virginia	WV	ACA Expansion	01/01/2014	12.8	T [2014]	Full	Consistent
Wisconsin[22]	WI	New eligibility for BadgerCare but not ACA Expansion	2009	5.5	Excluded	Substantial	Consistent
Wyoming	WY	None		3.6	C [.]	None	Consistent

[19] In 2008, Oregon enacted a small Medicaid expansion for low-income adults through a lottery among applicants. However, less than one-third of the 90,000 people on the waitlist were selected to apply for Medicaid in 2008 (Baicker et al., 2013), some of the denied applicants were then enrolled in 2010. We treat Oregon as full expansion due to the small size of this earlier expansion.

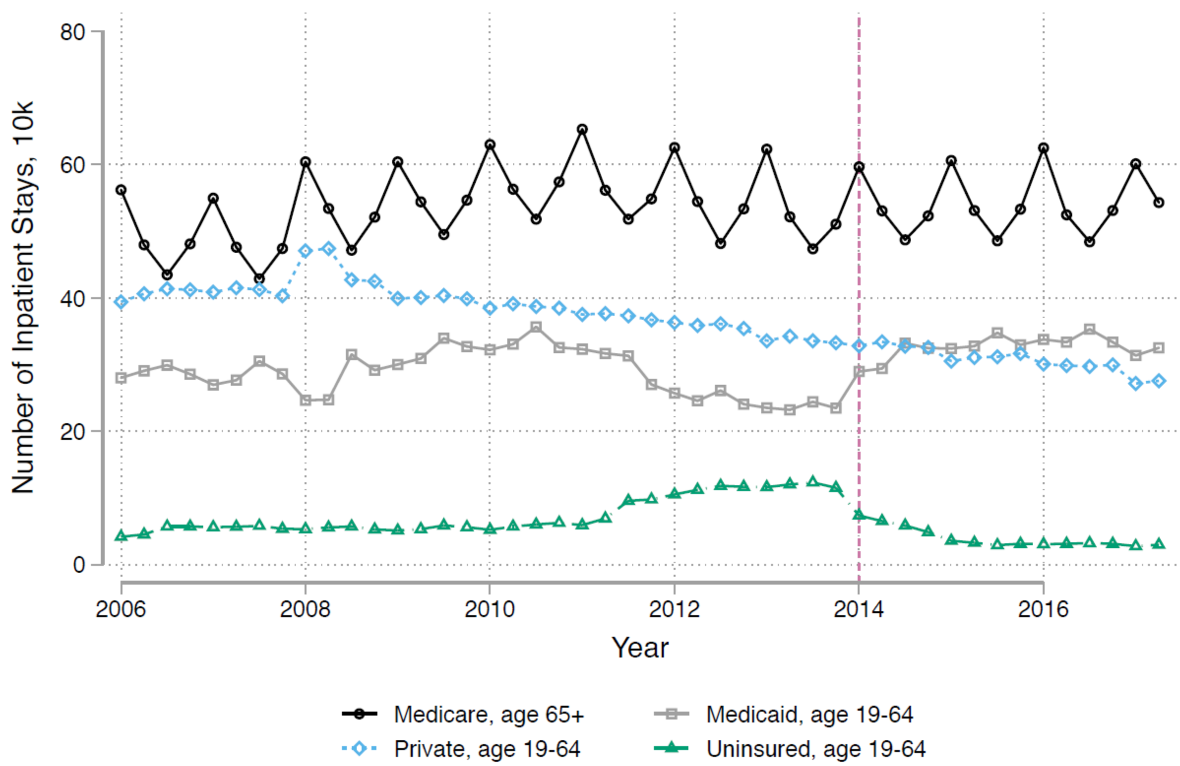
[20] In Vermont, childless adults up to 150% FPL were eligible for Medicaid equivalent coverage through the Vermont Health Access Plan waiver program (Heberlein et al., 2011). Vermont Health Access Plan (Sec. 1115 waiver) was approved in 1995 and effective in 1996.

[21] Washington's early expansion was limited to prior state plan enrollees (Sommers et al., 2013).

[22] Wisconsin received federal approval to offer Medicaid to childless adults below 100% FPL through the BadgerCare program as of 2009 (Gates & Rudowitz, 2014); it did not formally adopt ACA expansion in 2014 and kept the income threshold at 100% FPL.

Arizona Details for Table A-1

Arizona had a S.1931 program providing Medicaid up to 106% FPL for parents. It also had a limited program for childless adults, under a § 1115 waiver, starting in 2001, which was closed to new entrants since 2011.[23] Whether to treat Arizona as a full expansion state or an early expansion state turns on how many childless adults were still covered at the ACA onset in 2014, given churn in eligibility. The tail off in hospital admissions with Medicaid payment, and jump at the start of 2014 (with uninsured admissions showing the opposite pattern), persuades us that Arizona should be treated as a regular expansion state.



Source: Author reproduction of HCUP figure using HCUP Fast Stats at https://www.hcup-us.ahrq.gov/faststats/StatePayerServlet?state1=AZ.

[23] Source: https://www.kff.org/medicaid/fact-sheet/proposed-changes-to-medicaid-expansion-in-arizona/.

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Table A-2. Covariate Balance for Full-Expansion and Non-Expansion States

Table shows summary statistics for county-level covariates and mortality for Full-Expansion and Non-Expansion states during pre-expansion period (means over 2009-2013), using county population weights. *t*-statistics use two-sample *t*-test for difference and robust standard errors with state clusters. Normalized difference is a sample-size independent measure of the difference between two means, scaled by standard deviation): $ND_j = (\bar{x}_{jt} - \bar{x}_{jc}) / [(s_{jt}^2 + s_{jc}^2)/2]^{1/2}$. State groups are defined in Table A-1. Mortality rates are per 100,000 persons. Dollar amounts are in 2010 $.

	Full-Expansion States (1)	Non-Expansion States (2)	Difference t-stat (3)	Normalized Difference (4)
% age 0-19	23.36	24.35	1.11	-0.30
% age 18-34	22.74	23.42	1.40	-0.15
% age 35-44	12.94	13.11	0.71	-0.11
% age 45-54	14.53	13.98	2.32	0.40
% age 55-64	12.56	11.81	2.05	0.36
% age 65-74	7.56	7.48	0.16	0.04
% age 75-84	4.38	4.19	0.52	0.13
% age 85+	1.94	1.66	1.53	0.32
% Male	49.21	49.13	0.47	0.04
% White	82.91	77.43	2.19	0.36
% Black	11.42	18.16	2.61	-0.49
% Other Races	5.67	4.41	1.35	0.15
% Hispanic	11.44	16.33	0.87	-0.38
% In Poverty	14.67	16.89	2.75	-0.36
% Managed Care Penetration	24.55	22.99	0.42	0.15
% Disabled (ages 18-64)	16.31	17.57	1.29	-0.20
Mean Per Capita Income	40,208	37,537	1.72	0.31
Median Household Income	51,691	47,122	1.81	0.44
Unemployment Rate, 16+	8.84	8.28	1.12	0.20
% with Diabetes	8.85	9.72	2.45	-0.46
% Physically Inactive	22.89	24.70	1.85	-0.40
% Obese	27.95	29.11	1.16	-0.28
% Smoker	21.96	21.71	0.27	0.06
Physicians/1,000 people	3.10	2.65	2.88	0.27
% Uninsured (ages 18-64)	18.68	24.96	3.36	-1.09
Amenable Mortality (all ages)	510.52	481.21	0.90	0.18
Amenable Mortality (ages 55-64)	575.22	623.78	1.86	-0.24
Non-amenable Mortality (all ages)	345.28	341.33	0.20	0.04
Non-amenable Mortality (ages 55-64)	278.85	309.76	2.50	-0.30

Table A-3: DD and Triple-Difference Estimates: Different Demographic Groups (ages 55-64)

First column shows annual averages over 2009-2016 for number of deaths and population in millions. Of the full sample (28.8M people), 14.5M were in expansion states. Second column shows mortality rate for persons aged 55-64 for indicated groups. Third column shows first-stage DD estimates of change in uninsurance rates (in percent) from 2013 to 2016 for indicated demographic subsamples, for persons aged 50-64, from regression of percent uninsurance on Full Expansion dummy, with state and year FE and state population weights, using state-level SAHIE data (best available), and same covariates as the DD and triple difference regressions. Remaining columns show coefficients from DD or triple difference regressions on Full-Expansion dummy or, for triple difference column, full-expansion dummy * age 55-64 dummy, from county-level regressions with county-and year FE and population weights, similar to Table 2, for *ln*((amenable mortality/100,000 persons)+1) over 2009-2015. Standard errors use state clusters. *.**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

Demographic Subsamples	**Ann. Deaths (Pop. in M) (1)**	**Mortality rate (2)**	**First stage (%) 50-64 yrs (3)**	**DiD 55-64 yrs (4)**	**DiD 65-74 yrs (5)**	**Triple diff. (6)**
All Amenable	174,379	605.3	**1.113****	**-0.018****	-0.008	-0.004
	(28.8)		**(0.452)**	**(0.008)**	(0.006)	(0.008)
Male	105,465	759.8	0.692	-0.018*	-0.004	-0.004
	(13.9)		(0.747)	(0.010)	(0.008)	(0.010)
Female	68,914	461.7	0.936	**-0.020****	-0.016*	0.004
	(14.9)		(0.705)	**(0.009)**	(0.009)	(0.012)
White (Not Hispanic)	129,542	589.8	**1.130****	-0.015*	-0.011*	-0.003
	(22.0)		**(0.490)**	(0.008)	(0.007)	(0.009)
Black (Not Hispanic)	32,217	917.0	0.994	-0.031*	0.020	**-0.055*****
	(3.5)		(0.852)	(0.016)	(0.015)	**(0.017)**
Other	3,619	321.6	-	-0.050	-0.039	-0.035
	(1.1)		-	(0.060)	(0.052)	(0.078)
Hispanic	9,086	398.2	1.484	**-0.161*****	-0.092	-0.055*
	(2.3)		(1.228)	**(0.057)**	(0.057)	(0.029)
Not Hispanic	165,293	623.1	-	**-0.018****	-0.008	-0.005
	(26.5)		-	**(0.008)**	(0.006)	(0.007)
Pop. Weights			Yes	Yes	Yes	Yes
Covariates			Yes	Yes	Yes	Yes

Table A-4: DD and Triple-Difference Estimates: by Educational Attainment (ages 45-64)

First column shows annual averages over 2009-2016 for number of deaths and population in millions. Second column shows mortality rate for persons aged 55-64 for indicated groups. Third column shows first-stage DD estimates of change in uninsurance rates (in percent) from 2013 to 2016 for indicated education-levels, for persons aged 45-64, from regression of percent uninsurance on Full Expansion dummy, with state and year FE and state population weights. Remaining columns show coefficients from DD or triple difference regressions on Full-Expansion dummy or, for triple difference column, full-expansion dummy * age 45-64 dummy, from county-level regressions with county and year FE and population weights, similar to Table 2, for *ln*((amenable mortality/100,000 persons)+1) among persons with indicated education levels, over 2009-2015. Standard errors use state clusters. *.**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

Education Subsample	**Ann. Deaths (Pop. in M) (1)**	**Mortality Rate (2)**	**First stage (%) 45-64 yrs (3)**	**DiD 45-64 yrs (4)**	**DiD 65+ yrs (5)**	**Triple diff. (6)**
All Amenable	252,285	422.1	1.048	-0.012	**-0.020*****	0.014
	(59.77)		(0.738)	(0.008)	**(0.006)**	(0.009)
Elementary School	14,776	565.4	3.747	0.047	0.014	0.066
	(2.61)		(2.530)	(0.046)	(0.058)	(0.048)
High School Incomplete	33,698	768.6	**3.912*****	-0.009	-0.003	-0.011
	(4.38)		**(1.449)**	(0.061)	(0.064)	(0.036)
High School Complete	110,019	607.2	1.533	-0.021	-0.032	0.010
	(18.12)		(0.939)	(0.040)	(0.037)	(0.014)
Some College	86,793	250.5	0.468	-0.015	-0.026	0.013
	(34.65)		(0.572)	(0.035)	(0.031)	(0.011)
Population Weights			Yes	Yes	Yes	Yes
Covariates			Yes	Yes	Yes	Yes

Table A-5: DD and Triple-Difference Estimates: by Cause of Death (age 55-64)

First column shows annual averages over 2009-2016 for number of deaths and population in millions. Second column shows mortality rate for persons aged 55-64 for indicated groups. Remaining columns show coefficients from DD or triple difference regressions on Full-Expansion dummy or, for triple difference column, full-expansion dummy * age 45-64 dummy, from county-level regressions with county and year FE and population weights, similar to Table 2, for *ln*((amenable mortality/100,000 persons)+1) among persons with indicated primary cause of death, over 2009-2016. Standard errors use state clusters. *.**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

By Cause of Death	deaths (pop. In M)	DiD 55-64 yrs	DiD 65-74 yrs	Triple diff.
	(1)	(2)	(3)	(4)
All Amenable	174,379	**-0.018****	-0.008	-0.004
	(28.81)	**(0.008)**	(0.006)	(0.008)
Cancer	87,170	-0.003	0.003	-0.004
	(28.81)	(0.006)	(0.006)	(0.009)
Diabetes	14,394	-0.024	0.001	-0.007
	(28.81)	(0.019)	(0.025)	(0.020)
Cardiovascular	70,677	-0.010	-0.009	0.006
	(28.81)	(0.010)	(0.010)	(0.010)
Respiratory	16,442	-0.030	-0.017	-0.010
	(28.81)	(0.020)	(0.013)	(0.023)
HIV	1,282	-0.058	0.005	-0.051
	(28.81)	(0.037)	(0.038)	(0.060)
Pop. Weights		Yes	Yes	Yes
Covariates		Yes	Yes	Yes

Table A-6: Triple Difference Estimates: Separating Counties by Baseline Health Uninsurance or Poverty Levels (age 55-64)

First column shows annual averages over 2009-2016 for number of deaths and population aged 55-64 in millions, for sample of high-versus low- uninsurance counties. Second and fourth columns column shows full-sample and by gender first stages; we lack the data to compute first stages for the other subsamples. Remaining columns show coefficients from triple difference, county-level regressions with county and year FE and population weights, similar to Table 2, over 2009-2016, for amenable mortality for full sample and indicated subsamples. Third difference in column (3) is between the counties with the highest uninsurance rate in 2013, containing 20% of the U.S. population, and the counties with the lowest uninsurance rate in 2013, containing 20% of the U.S. population. Third difference in column (5) is similar but is between the counties with lowest versus highest poverty rates in 2013. Standard errors use state clusters. *.**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

Sample	**Deaths (pop. in M) (1)**	**First Stage (%) 50-64 yrs (2)**	**Triple diff. Uninsurance (3)**	**First Stage (%) 50-64 yrs (4)**	**Triple diff. Poverty (5)**
All	66,329	1.221	0.003	0.720	0.000
	(11.9)	(0.653)	(0.020)	(0.789)	(0.013)
Male	40,750	0.593	-0.020	0.408	-0.024
	(5.8)	(0.657)	(0.028)	(0.721)	(0.018)
Female	26,103	**1.829*****	0.050*	0.912	**0.037*****
	(6.1)	**(0.679)**	(0.028)	(0.791)	**(0.014)**
White (Not Hispanic)	51,198		-0.017		-0.015
	(9.1)		(0.018)		(0.010)
Black (Not Hispanic)	11,970		-0.001		-0.073*
	(1.4)		(0.059)		(0.040)
Other	1,496		-0.083		-0.005
	(0.4)		(0.137)		(0.107)
Hispanic	3,421		0.279		0.082
	(0.9)		(0.267)		(0.103)
Not Hispanic	60,879		0.003		-0.005
	(10.4)		(0.021)		(0.015)
Pop. Weights		Yes	Yes	Yes	Yes
Covariates		Yes	Yes	Yes	Yes

Table A-7. Estimated Effect of Medicaid Expansion on Amenable Mortality: Different Specifications

Table 2 in the text shows DD and triple-difference estimates for county-level regressions, with county and year FE and population weights, of ln[(amenable mortality/100,000 persons)+1] over 2009-2016 on full-expansion dummy (=1 for Full-Expansion States in expansion years; 0 otherwise), and covariates. Third difference is ages 55-64 versus ages 65-74. This table provides results for principal coefficients of interest, from regressions in which we vary this specification as follows: Panel A reproduces our results from text Table 2; Panel B uses ATT*population weights instead of only population weights; Panel C adds linear state trends; Panel D reports results from regressions at state- instead of county-level (with population weights); and Panel E reports results from state-level regressions without weights. Standard errors use state clusters. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

	DiD 55-64 years		**Triple diff.**	
	(1)	**(2)**	**(3)**	**(4)**
Panel A. Main Specification (from text Table 2)				
Full Expansion Dummy	-0.018* (0.010)	**-0.018**** **(0.008)**		
Full Expansion Dummy x Age 55-64 Dummy			-0.002 (0.009)	-0.004 (0.008)
Panel B. With ATT x Population Weights				
Full Expansion Dummy	-0.014 (0.013)	-0.015* (0.009)		
Full Expansion Dummy x Age 55-64 Dummy			-0.014 (0.009)	-0.013 (0.012)
Panel C. With Linear State Trends				
Full Expansion Dummy	-0.006 (0.008)	-0.009 (0.008)		
Full Expansion Dummy x Age 55-64 Dummy			-0.001 (0.009)	-0.003 (0.008)
Panel D. State-Level (with Pop Weights)				
Full Expansion Dummy	**-0.020**** **(0.009)**	-0.011* (0.007)		
Full Expansion Dummy x Age 55-64 Dummy			-0.006 (0.008)	-0.009 (0.010)
Panel E. State-Level (No Weights) Specification				
Full Expansion Dummy	**-0.018**** **(0.009)**	-0.009 (0.009)		
Full Expansion Dummy x Age 55-64 Dummy			-0.009 (0.010)	-0.015 (0.011)
Covariates	No	Yes	No	Yes

Table A-8: Triple-Difference Estimates by Demographic Group: Different Specifications

Table 3 in the text shows DD and triple-difference estimates for different demographic groups, from county-level regressions, with county and year FE and population weights, of ln[(amenable mortality/100,000 persons)+1] over 2009-2016 on full-expansion dummy (=1 for Full-Expansion States in expansion years; 0 otherwise), and covariates. Third difference is ages 55-64 versus ages 65-74. This table provides triple difference results for principal coefficients of interest, from regressions in which we vary this specification as follows: using ATT*population weights; adding linear state trends; and running regressions at state- instead of county-level, with and without population weights. Standard errors use state clusters. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

	Triple Difference Results				
Subsamples	**Main Specification (1)**	**ATT x Pop weights (2)**	**with Linear State Trends (3)**	**State-Level w. pop. weights (4)**	**State-Level unweighted (5)**
All Amenable	-0.004	-0.013	-0.003	-0.009	-0.015
	(0.008)	(0.012)	(0.008)	(0.010)	(0.011)
Male	-0.004	-0.003	-0.003	-0.015	**-0.034****
	(0.010)	(0.022)	(0.010)	(0.012)	**(0.014)**
Female	0.004	-0.022	0.005	0.006	-0.003
	(0.012)	(0.015)	(0.011)	(0.013)	(0.014)
White (Not Hispanic)	-0.003	-0.010	-0.002	-0.015	-0.002
	(0.009)	(0.010)	(0.009)	(0.011)	(0.011)
Black (Not Hispanic)	**-0.055*****	**-0.345****	**-0.055*****	**-0.040*****	0.010
	(0.017)	**(0.172)**	**(0.017)**	**(0.014)**	(0.124)
Other	-0.035	0.168	-0.036	-0.056	-0.038
	(0.078)	(0.269)	(0.078)	(0.036)	(0.059)
Hispanic	-0.055*	-0.153	-0.050*	-0.016	0.054
	(0.029)	(0.153)	(0.027)	(0.023)	(0.156)
Not Hispanic	-0.005	-0.013	-0.004	-0.010	-0.012
	(0.007)	(0.012)	(0.007)	(0.008)	(0.011)
Weights	Pop	ATT x Pop	Pop	Pop	No
Covariates	Yes	Yes	Yes	Yes	Yes

Table A-9: Triple-Difference Estimates by Educational Attainment (ages 45-64) - Different Specifications

Table 4 in the text shows DD and triple-difference estimates for groups with different education levels, from county-level regressions, with county and year FE and population weights, of ln[(amenable mortality/100,000 persons)+1] over 2009-2016 on full-expansion dummy (=1 for Full-Expansion States in expansion years; 0 otherwise), and covariates. Third difference is ages 55-64 versus ages 65-74. This table provides triple difference results for principal coefficients of interest, from regressions in which we vary this specification as follows: using ATT*population weights; adding linear state trends; and running regressions at state- instead of county-level, with and without population weights. Standard errors use state clusters. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

	Triple Difference Results				
Education Subsamples	**Main Specification (1)**	**ATT x Pop weights (2)**	**with Linear State Trends (3)**	**State-Level w. pop. weights (4)**	**State-Level unweighted (5)**
All Amenable	0.014	-0.001	0.014	0.007	0.007
	(0.009)	(0.011)	(0.009)	(0.009)	(0.010)
Elementary School	0.066	0.129*	0.045	0.045	0.062
	(0.048)	(0.068)	(0.046)	(0.031)	(0.040)
High School Incomplete	-0.011	-0.015	0.004	-0.023	-0.039
	(0.036)	(0.031)	(0.036)	(0.031)	(0.035)
High School Complete	0.010	-0.001	0.023	0.005	-0.017
	(0.014)	(0.021)	(0.019)	(0.013)	(0.023)
Some College	0.013	0.011	0.031*	0.011	0.005
	(0.011)	(0.018)	(0.017)	(0.013)	(0.023)
Weights	Pop	ATT x Pop	Pop	Pop	No
Covariates	Yes	Yes	Yes	Yes	Yes

Table A-10: Triple-Difference Estimates by Cause of Death (ages 55-64): Different Specifications

Table 5 in the text shows DD and triple-difference estimates for different causes of death, from county-level regressions, with county and year FE and population weights, of ln[(amenable mortality/100,000 persons)+1] over 2009-2016 on full-expansion dummy (=1 for Full-Expansion States in expansion years; 0 otherwise), and covariates. Third difference is ages 55-64 versus ages 65-74. This table provides triple difference results for principal coefficients of interest, from regressions in which we vary this specification as follows: using ATT*population weights; adding linear state trends; and running regressions at state- instead of county-level, with and without population weights. Standard errors use state clusters. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

	Triple Difference Results				
Cause of Death	**Main Specification (1)**	**ATT x Pop weights (2)**	**with Linear State Trends (3)**	**State-Level w. pop. weights (4)**	**State-Level unweighted (5)**
Amenable	-0.004	-0.013	-0.003	-0.009	-0.015
	(0.008)	(0.012)	(0.008)	(0.010)	(0.011)
Non-Amenable	-0.006	-0.008	-0.006	-0.006	-0.005
	(0.012)	(0.017)	(0.012)	(0.012)	(0.012)
Cancer	-0.004	-0.017	-0.004	-0.006	-0.001
	(0.009)	(0.011)	(0.008)	(0.010)	(0.011)
Diabetes	-0.007	-0.034	-0.005	-0.016	0.018
	(0.020)	(0.025)	(0.020)	(0.016)	(0.030)
Cardiovascular	0.006	-0.005	0.007	-0.002	-0.022
	(0.010)	(0.016)	(0.010)	(0.011)	(0.016)
Respiratory	-0.010	0.003	-0.009	-0.013	-0.023
	(0.023)	(0.035)	(0.022)	(0.016)	(0.026)
HIV	-0.051	-0.022	-0.051	-0.030	0.112
	(0.060)	(0.078)	(0.060)	(0.058)	(0.112)
Weights	Pop	Att x Pop	Pop	Pop	No
Covariates	Yes	Yes	Yes	Yes	Yes

Table A-11: Triple Difference Estimates: Counties with high-vs-low Baseline Health Uninsurance and Poverty Levels: Different Specifications

Table 6 in the text shows DD and triple-difference estimates for high-vs-low pre-ACA uninsurance and high-vs-low poverty counties, from county-level regressions, with county and year FE and population weights, of ln[(amenable mortality/100,000 persons)+1] over 2009-2016 on full-expansion dummy (=1 for Full-Expansion States in expansion years; 0 otherwise), and covariates. Third difference is ages 55-64 versus ages 65-74. This table provides triple difference results for principal coefficients of interest, from regressions in which we vary this specification as follows: using ATT*population weights; and comparing all non-elderly adults (ages 18-64) to all elderly (age 65+). Standard errors use state clusters. *, **, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively; significant results at 5% level or better in **boldface**.

	Triple Difference Results					
	Main Specification		**ATT x Pop Weights**		**Age 18-64 vs. 65+**	
Subsamples	**Unins.**	**Poverty**	**Unins.**	**Poverty**	**Unins.**	**Poverty**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
All Amenable	0.003	0.000	-0.023	-0.018	0.004	0.012
	(0.020)	(0.013)	(0.025)	(0.016)	(0.014)	(0.012)
Male	-0.020	-0.024	-0.045	**-0.046****	-0.025	-0.004
	(0.028)	(0.018)	(0.038)	**(0.020)**	(0.017)	(0.016)
Female	0.050*	**0.037*****	0.024	0.025	**0.054*****	**0.034****
	(0.028)	**(0.014)**	(0.036)	(0.039)	**(0.020)**	**(0.013)**
White (Not Hispanic)	-0.017	-0.015	**-0.053****	**-0.030*****	-0.027*	0.002
	(0.018)	(0.010)	**(0.024)**	**(0.010)**	(0.014)	(0.011)
Black (Not Hispanic)	-0.001	-0.073*	0.393	-0.303	-0.004	**-0.083*****
	(0.059)	(0.040)	(0.365)	(0.385)	(0.038)	**(0.032)**
Other	-0.083	-0.005	-0.354	-0.614	-0.057	0.060
	(0.137)	(0.107)	(0.411)	(0.512)	(0.079)	(0.074)
Hispanic	0.279	0.082	0.369	-0.004	0.056	-0.002
	(0.267)	(0.103)	(0.286)	(0.175)	(0.068)	(0.044)
Not Hispanic	0.003	-0.005	-0.028	-0.019	0.005	0.010
	(0.021)	(0.015)	(0.030)	(0.017)	(0.018)	(0.013)
Weights	Pop	Pop	Att x Pop	Att x Pop	Pop	Pop
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

Table A-12: Synthetic Control Method: Weights on Donor States

Table shows the weights assigned to the Non-Expansion States (donor states)by the regular synthetic control method, used in text Figure 3.

Non-Expansion States	Synthetic Control Weights
Alabama	0
Florida	0.123
Georgia	0
Idaho	0
Kansas	0
Louisiana	0
Maine	0.038
Mississippi	0
Missouri	0.411
Nebraska	0
North Carolina	0
Oklahoma	0
South Carolina	0
South Dakota	0
Tennessee	0
Texas	0.023
Utah	0.041
Virginia	0.272
Wyoming	0.091

Figure A-1. Time Trends in Amenable Mortality for Persons Aged 18-64

Figure shows amenable mortality rate for persons age 18-64 for Full-Expansion, Substantial Expansion, Mild Expansion, and Non-Expansion States, over 1999-2016, using county population weights. State groups are defined in Table 1. Dashed vertical line separate pre-expansion from expansion period.

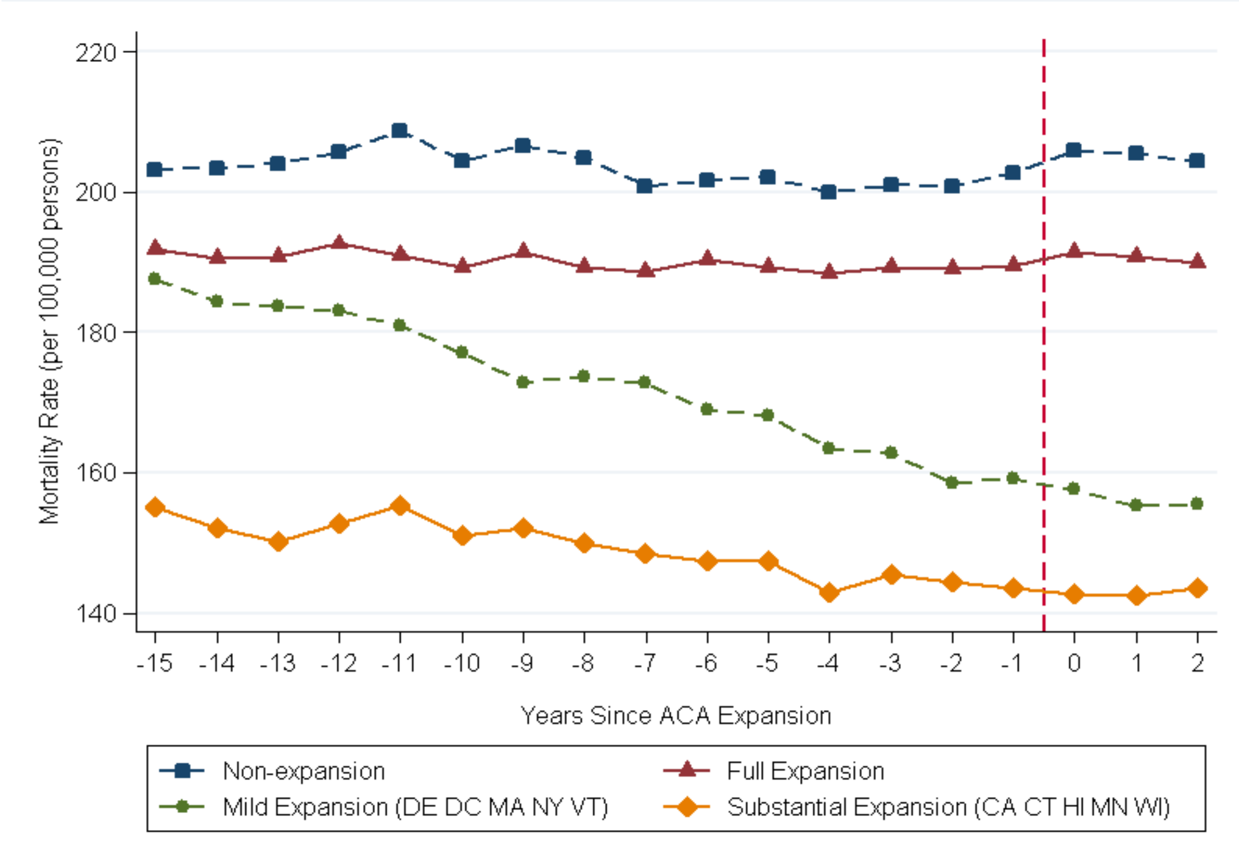


Figure A-2. Synthetic Control Results for Near-Elderly Amenable Mortality

Synthetic control results for *ln*((amenable mortality/100,000 persons)+1) for Full-Expansion States (treated as a single treated unit) versus synthetic control drawn from Non-Expansion States, over 1999-2016. Covariates for constructing donor pool are same as in Figure 2, plus uninsurance rate in 2013. The y-axis shows *ln*((amenable mortality/100,000 persons)+1) for Full-Expansion States, combined into single treated unit (using population weights), and their synthetic control. Vertical dotted line separates pre-expansion from expansion period.

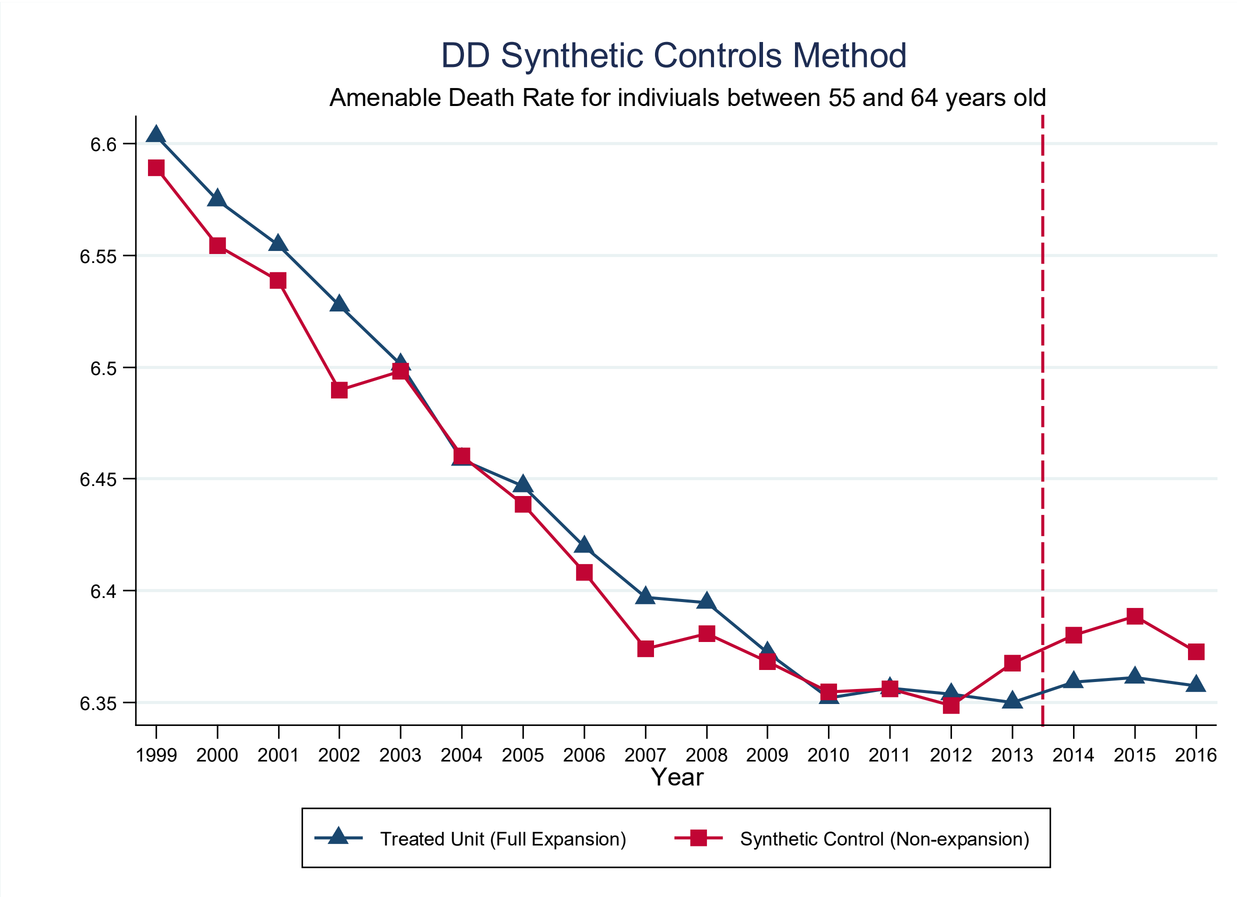


Figure A-3. Generalized Synthetic Control Method (gsynth)

Synthetic control results, using Xu's (2017) generalized synthetic control (gsynth) method, for *ln*(amenable mortality/100,000 + 1) for Full-Expansion States versus synthetic control for each state over 1999-2015. The donor pool consists of every non-expansion state's 55 to 64 year-old death rate as well as every state's untreated 65 to 74 year old population. This design is intended to crudely approximate triple-difference results. States are equally weighted. Covariates for constructing synthetic control are same as in the specifications with covariates in Table 2 of the text. The y-axis shows coefficient on Full-Expansion dummy. Vertical bars around point estimates show 95% CIs. Dashed vertical line separates pre-expansion from expansion period.

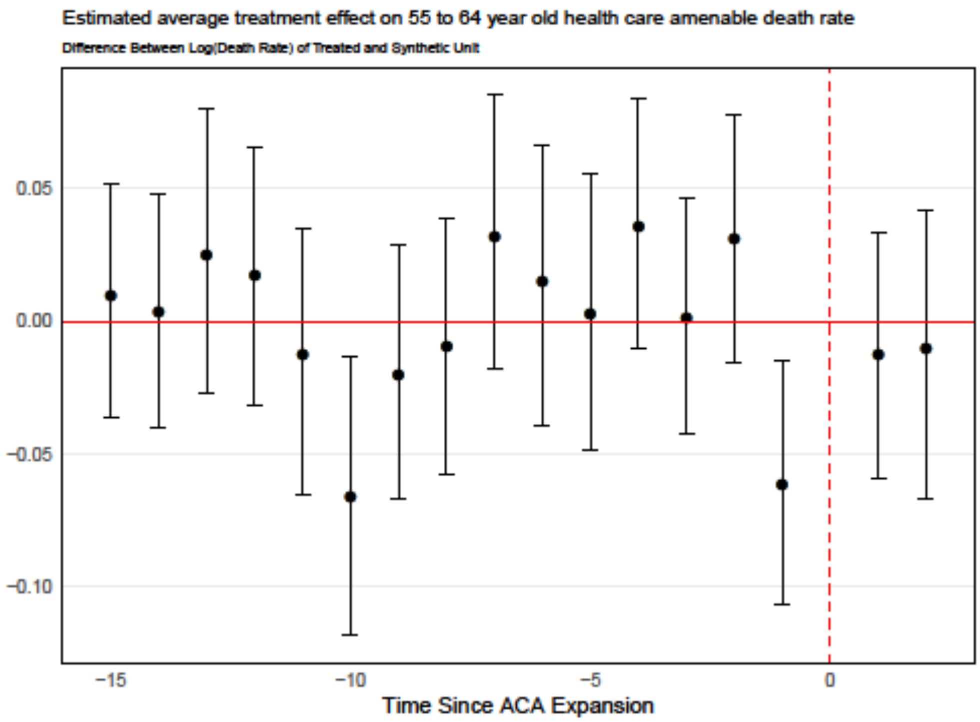
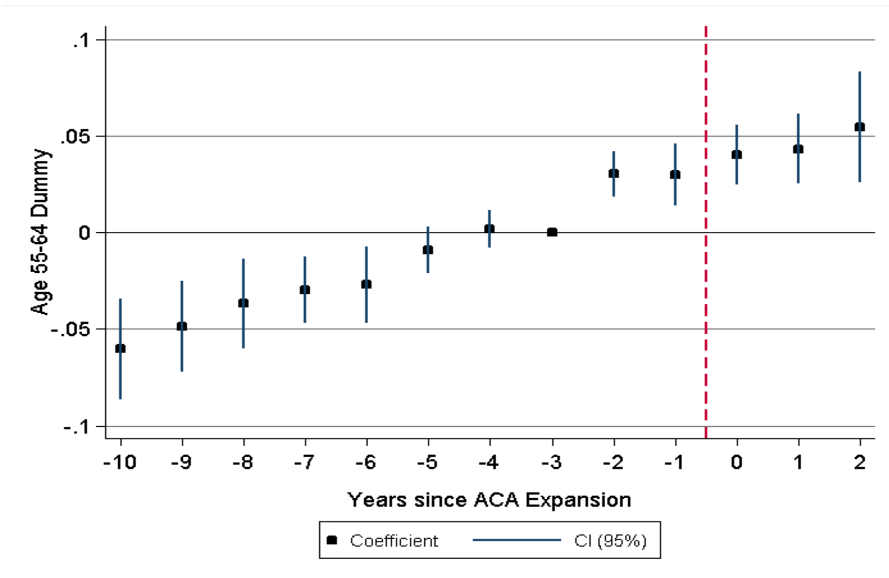


Figure A-4. Age Discontinuity Leads-and-Lags Results, Separately for Full-Expansion and No-Expansion States

Graphs from leads-and-lags regressions of *ln*((amenable mortality/100,000 persons)+1) for 55-64 versus 65-74 age groups in Full-Expansion (Panel A) and No-Expansion States (Panel B), over 2004-2016. Covariates are listed in paper. Regressions include county and year FE, and county-population weights. y-axis shows coefficients on lead and lag dummies; vertical bars show 95% confidence intervals (CIs) around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero.

Panel B. Amenable Mortality in Full-Expansion-States



Panel B. Amenable Mortality in No Expansion-States

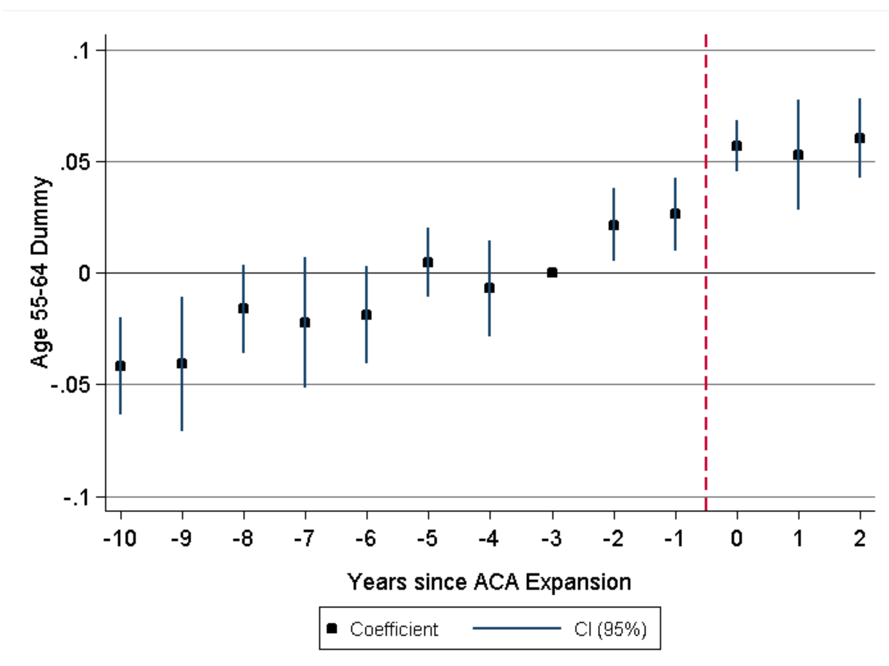


Figure A-5. Triple Difference Leads-and-Lags Graphs: Demographic Groups

Graphs from leads and lags regressions of triple differences for indicated subsamples, of *ln*((amenable mortality/100,000 persons)+1) for persons aged 55-74, in Full-Expansion States versus No-Expansion States, over 2004-2016; the third difference is age 55-64 versus age 65-74. Covariates are same as in Figure 2. Regressions include county and year FE, and county-population weights. y-axis shows coefficients on lead and lag dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero.

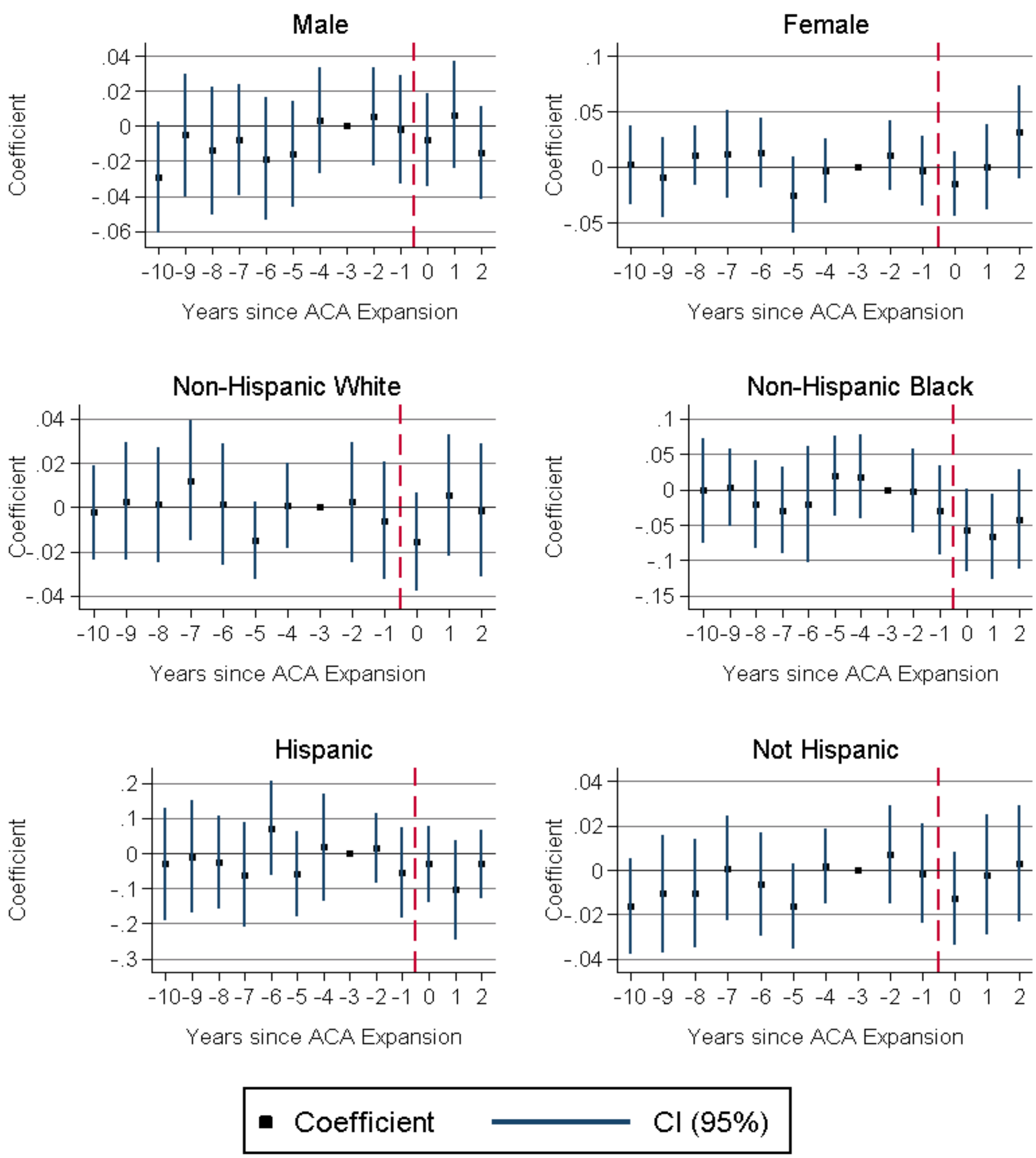


Figure A-6. Triple Difference Leads-and-Lags Graphs: By Education Level

Graphs show leads and lags regressions of triple differences for indicated subsamples, of *ln*((amenable mortality/100,000 persons)+1) for persons aged 45+, in Full-Expansion States versus No-Expansion States, over 2004-2016; the third difference is age 45-64 versus age 65+. Covariates are same as in Figure 2. Regressions include county and year FE, and county-population weights. y-axis shows coefficients on lead and lag dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero.

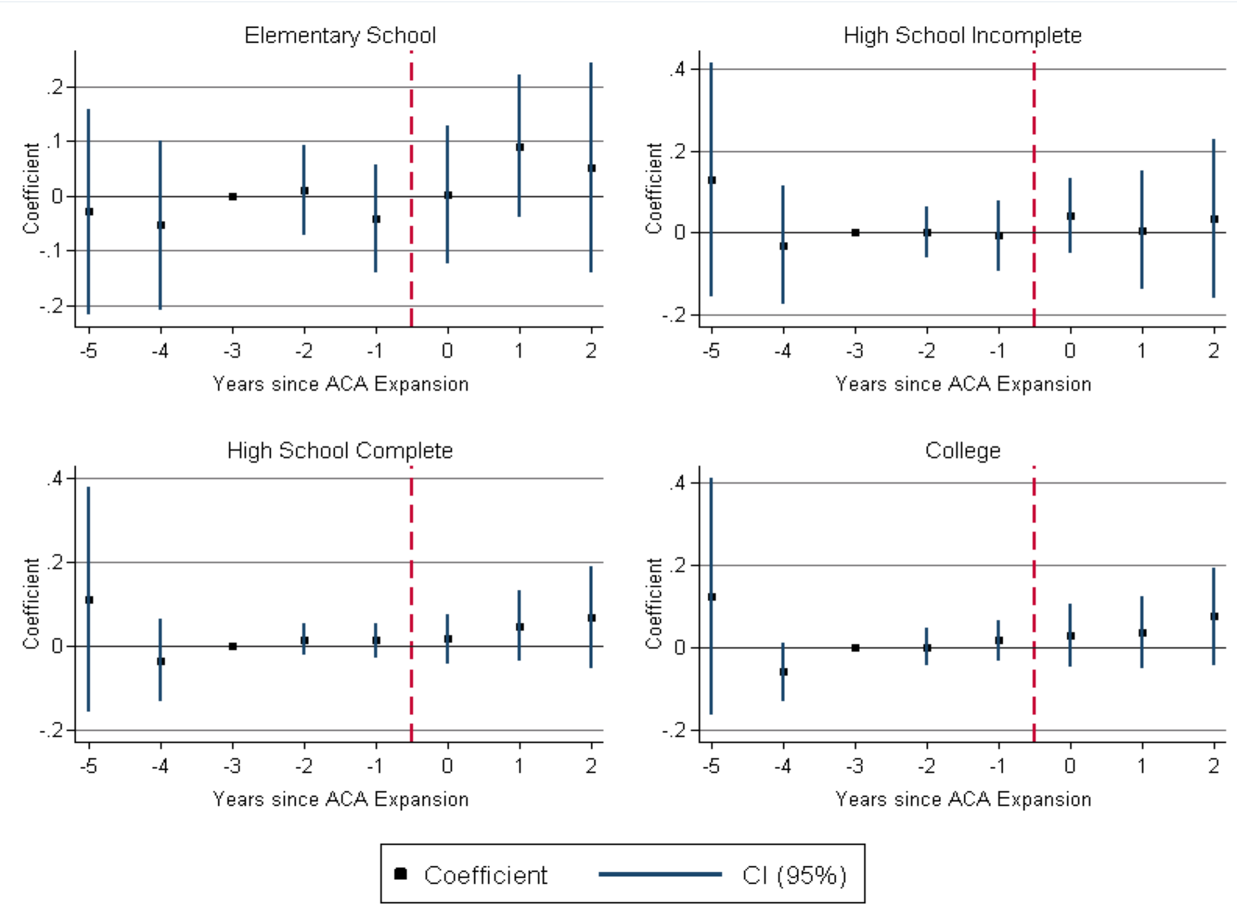


Figure A-7. Triple Difference Leads-and-Lags Graphs: By Causes of Death

Graphs show triple difference leads and lags regressions of *ln*[(mortality/100,000 persons)+1] among persons with indicated primary cause of death, aged 55-74, in Full-Expansion States versus No-Expansion States, over 2004-2016; the third difference is age 55-64 versus age 65-74. Covariates are listed in the paper. Regressions include county and year FE, and county population weights. Y-axis shows coefficients on leads and lags dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

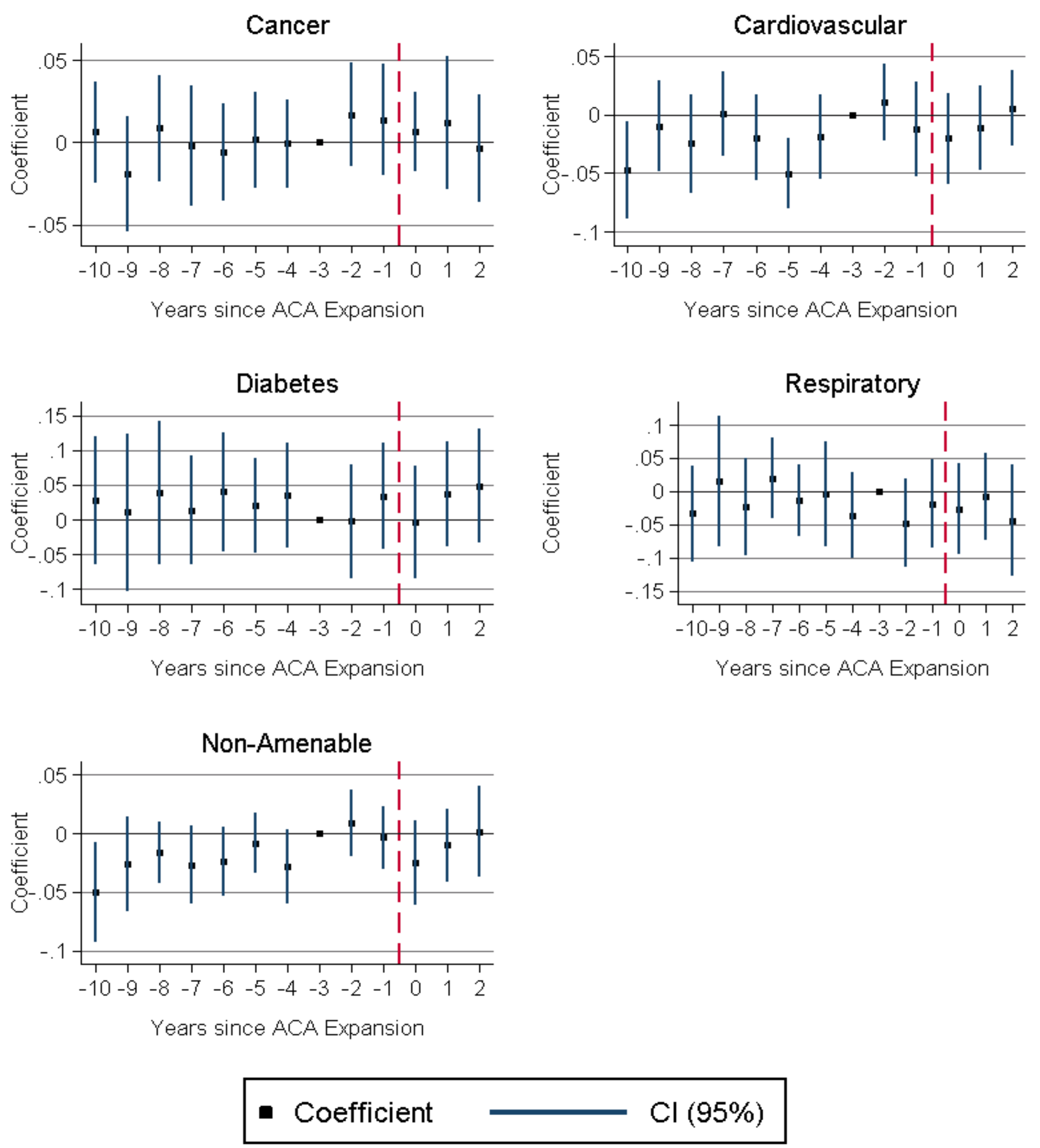
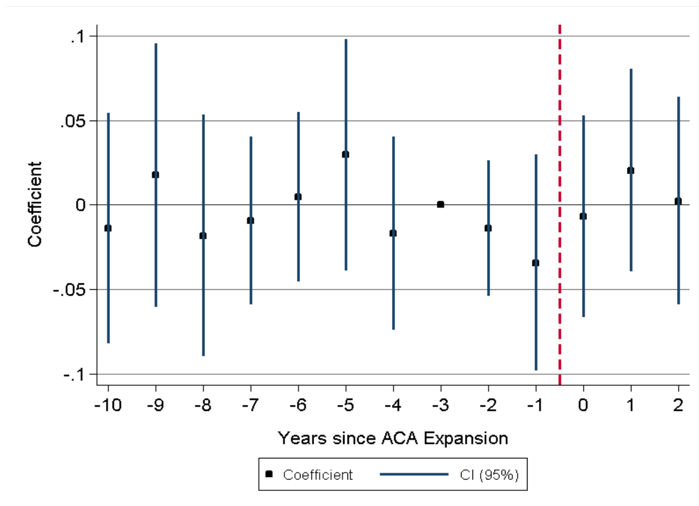


Figure A-8: Leads and Lags Graphs for High-vs-Low Uninsurance and Poverty

Graphs show leads and lags regressions of triple differences for high versus low uninsurance and high vs. low poverty counties, of *ln*((amenable mortality/100,000 persons)+1+ for persons aged 55-64, in Full-Expansion States versus No-Expansion States, over 2004-2016. High (low) uninsurance counties are those with highest (lowest) uninsurance rates in 2013 containing 20% of U.S. population, and similarly for high (low) poverty counties. Covariates are same as in Figure 2. Regressions include county and year FE, and county-population weights. y-axis shows coefficients on lead and lag dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero.

Panel A. High-Uninsurance vs. Low-Uninsurance Counties



Panel B. High-Poverty vs. Low-Poverty Counties

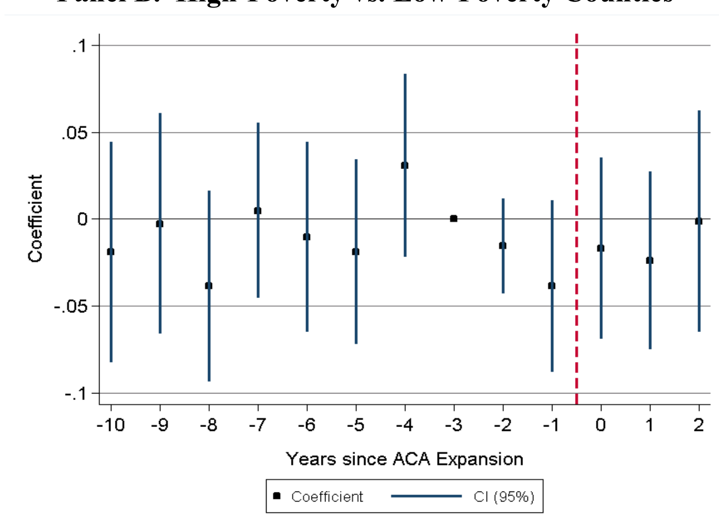
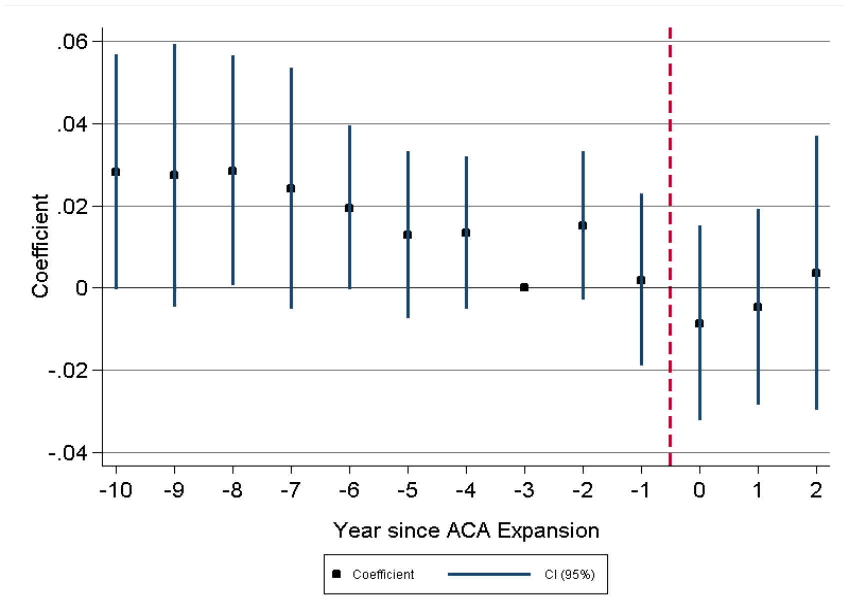


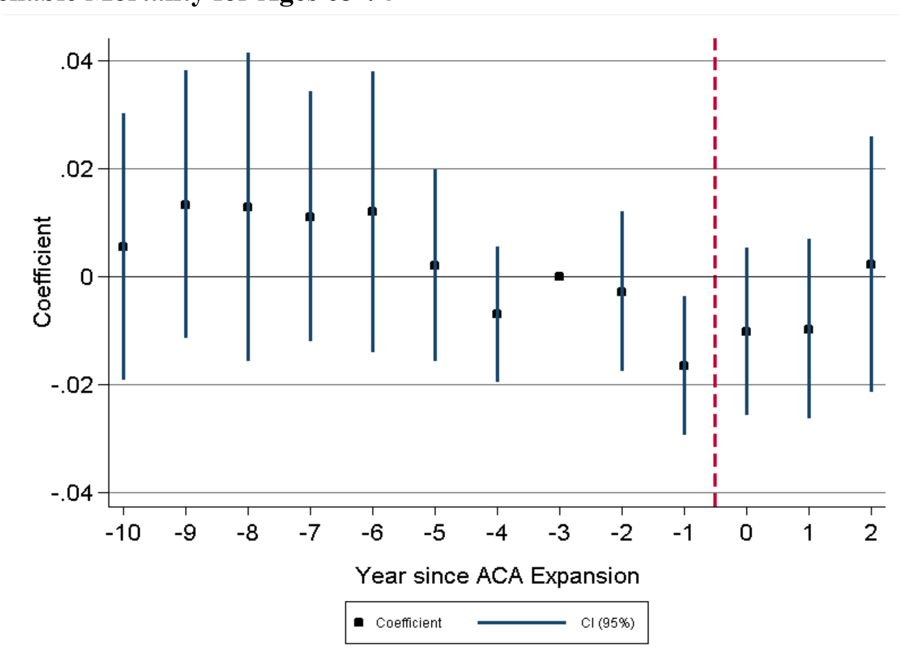
Figure A-9. DiD and Triple Difference Leads-and-Lags Results: Amenable Mortality, with ATT x Population Weights

Graphs from leads and lags regressions of *ln*[(amenable mortality/100,000 persons)+1] for Full-Expansion States versus control group of Non-Expansion States, over 2004-2016. Covariates are listed in paper. Regressions include county and year FE, and ATT x Population weights. Y-axis shows coefficients on lead and lag dummies; vertical bars show 95% confidence intervals (CIs) around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

Panel A. Amenable Mortality for Ages 55-64



Panel B. Amenable Mortality for Ages 65-74



Panel C. Triple difference. Leads and lags graphs for amenable mortality for persons age 55-64 in Full-Expansion States, relative to (i) persons age 65-74 in Full-Expansion States, and (ii) persons age 55-64 in Non-Expansion States.

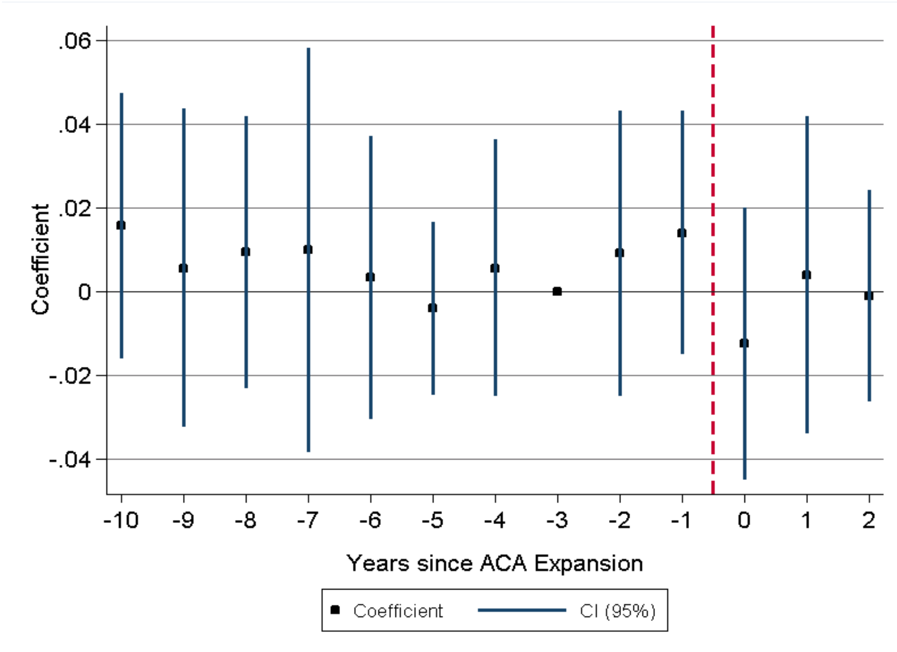
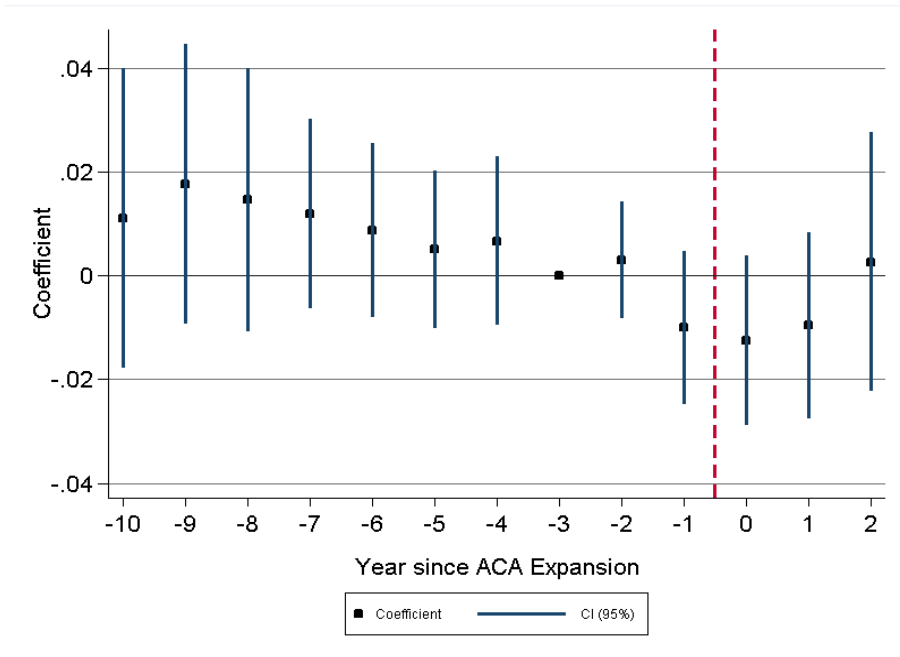


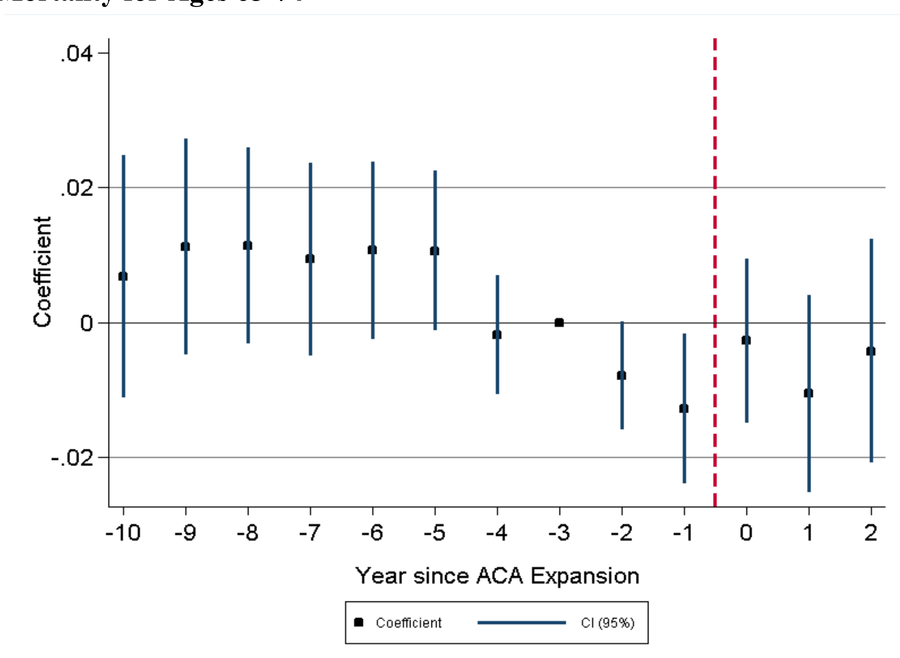
Figure A-10. DiD and Triple Difference Leads-and-Lags Results for Total Mortality

Graphs from leads and lags regressions of *ln*[(all mortality/100,000 persons)+1] for Full-Expansion States versus control group of Non-Expansion States, over 2004-2016. Covariates are listed in paper. Regressions include county and year FE, and county-population weights. Y-axis shows coefficients on lead and lag dummies; vertical bars show 95% confidence intervals (CIs) around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

Panel A. All Mortality for Ages 55-64



Panel B. All Mortality for Ages 65-74



Panel C. Triple difference. Leads and lags graphs for all mortality for persons age 55-64 in Full-Expansion States, relative to (i) persons age 65-74 in Full-Expansion States, and (ii) persons age 55-64 in Non-Expansion States.

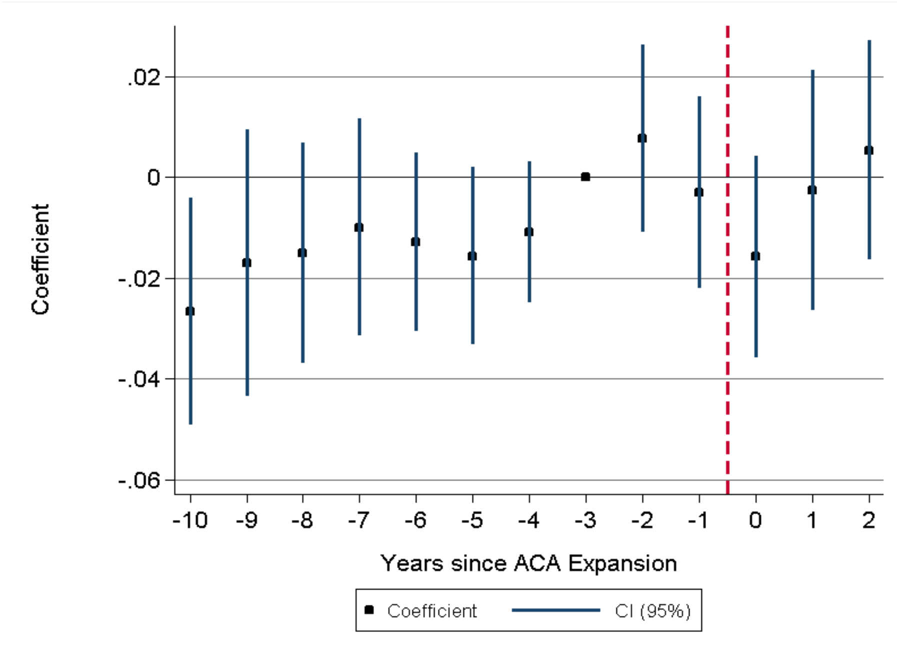
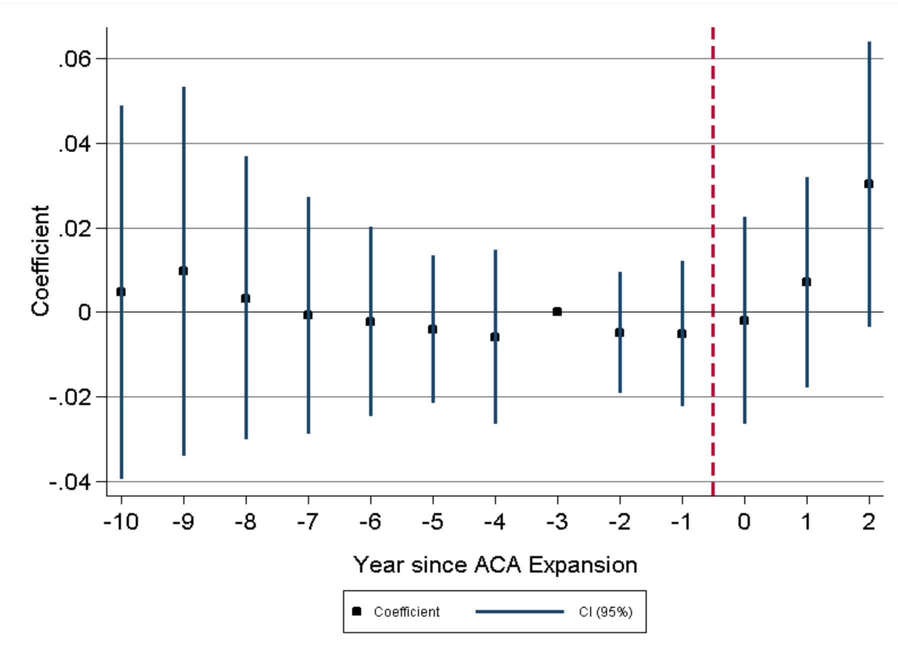


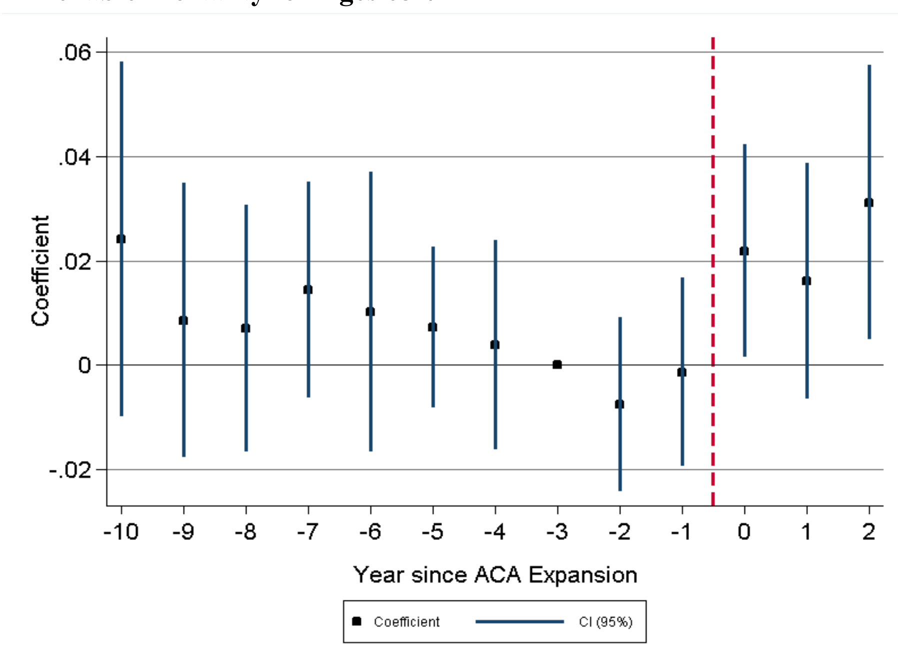
Figure A-11. DiD and Triple Difference Leads-and-Lags Results for Non-Amenable Mortality

Graphs from leads and lags regressions of *ln*[(non-amenable mortality/100,000 persons)+1] for Full-Expansion States versus control group of Non-Expansion States, over 2004-2016. Covariates are listed in paper. Regressions include county and year FE, and county-population weights. Y-axis shows coefficients on lead and lag dummies; vertical bars show 95% confidence intervals (CIs) around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

Panel A. Non-Amenable Mortality for Ages 55-64



Panel B. Non-Amenable Mortality for Ages 65-74



Panel C. Triple difference. Leads and lags graphs for non-amenable mortality for persons age 55-64 in Full-Expansion States, relative to (i) persons age 65-74 in Full-Expansion States, and (ii) persons age 55-64 in Non-Expansion States.

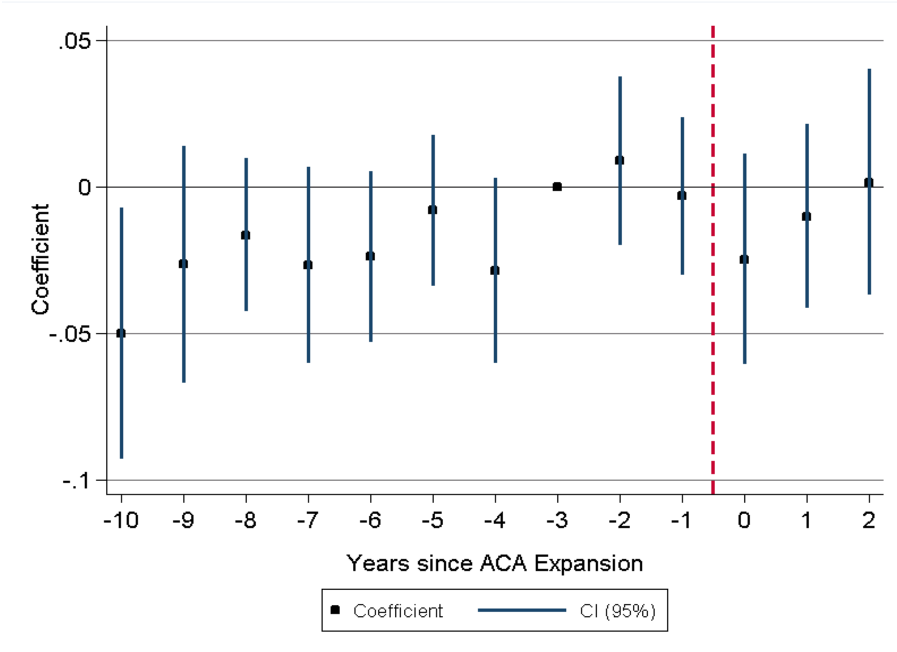


Figure A-12. Triple Difference Leads-and-Lags Graphs: Demographic Groups, with ATT x Population Weights

Graphs from leads and lags regressions of triple differences for indicated subsamples, of *ln*[(amenable mortality/100,000 persons)+1] for persons aged 55-74, in Full-Expansion States versus No-Expansion States, over 2004-2016; the third difference is age 55-64 versus age 65-74. Covariates are listed in the paper. Regressions include county and year FE, and Att x Pop weights. Y-axis shows coefficients on lead and lag dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

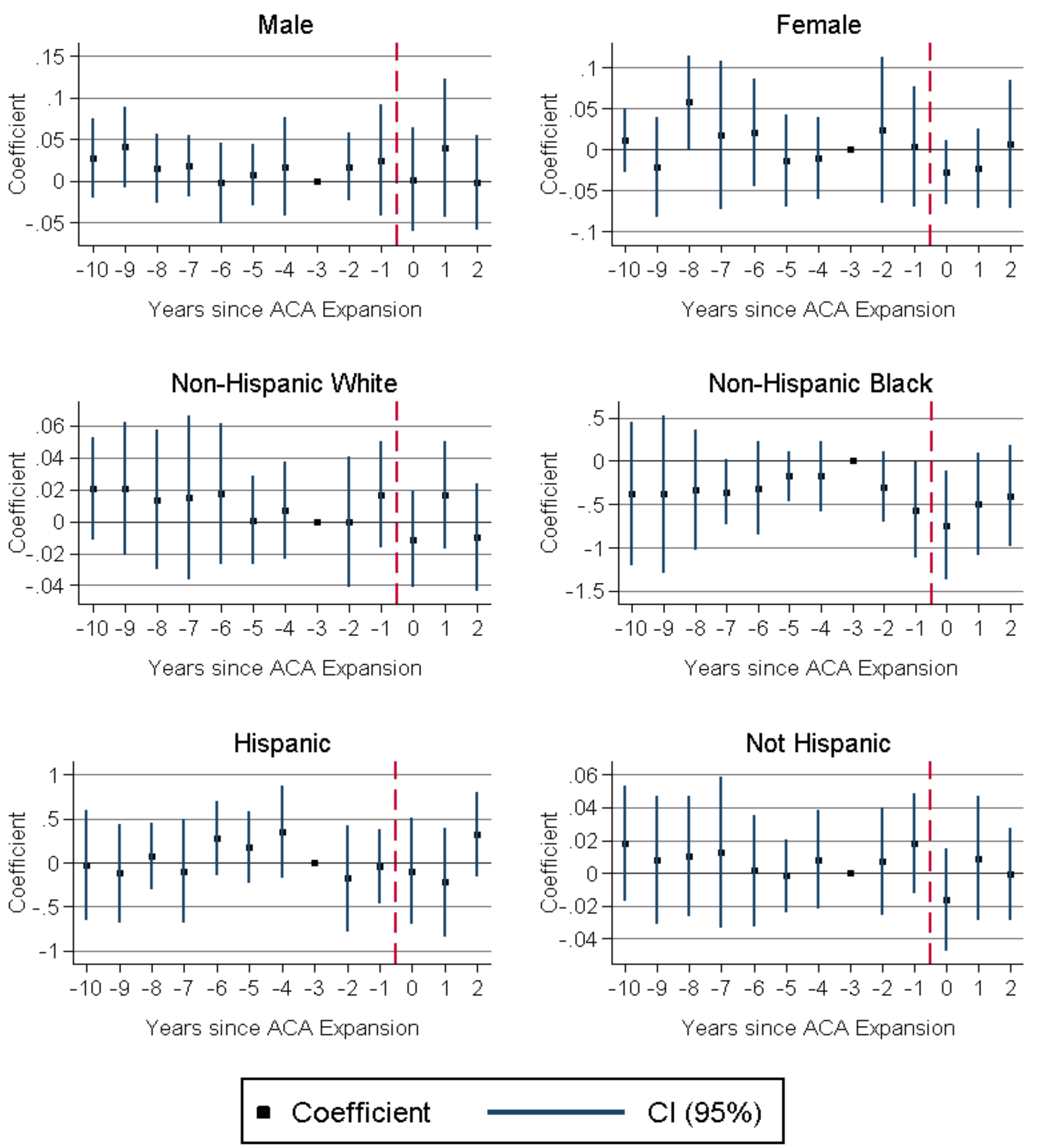


Figure A-13. Triple Difference Leads-and-Lags Graphs: By Education Level, with ATT x Population Weights

Graphs show leads and lags regressions of triple differences for indicated subsamples, of *ln*[(amenable mortality/100,000 persons)+1] for persons aged 45+, in Full-Expansion States versus No-Expansion States, over 2004-2016; the third difference is age 45-64 versus age 65+. Covariates are listed in the paper. Regressions include county and year FE, and ATT x Population weights. y-axis shows coefficients on lead and lag dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

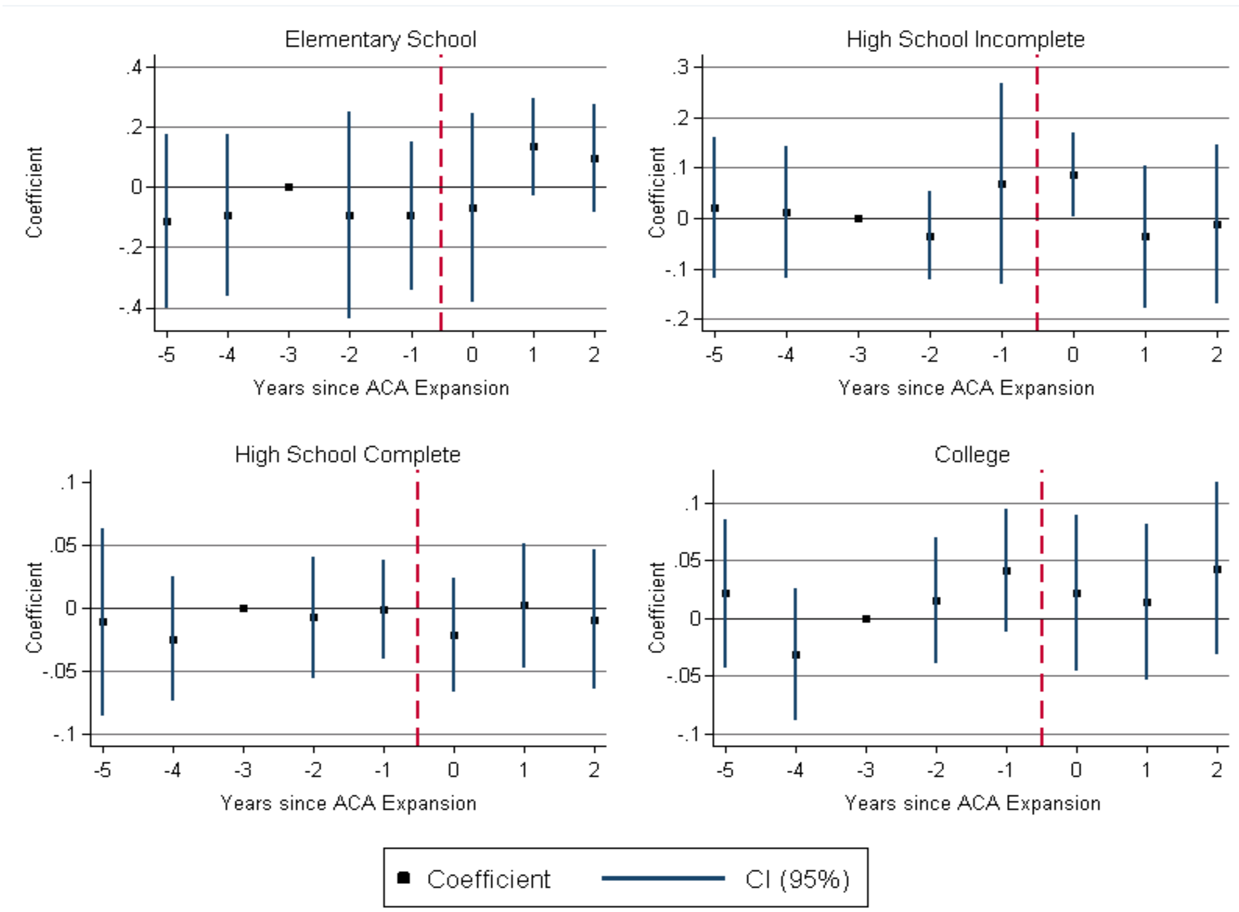


Figure A-14. Triple Difference Leads-and-Lags Graphs: By Causes of Death, ATT x Population Weights

Graphs show triple difference leads and lags regressions of *ln*[(mortality/100,000 persons)+1] among persons with indicated primary cause of death, aged 55-74, in Full-Expansion States versus No-Expansion States, over 2004-2016; the third difference is age 55-64 versus age 65-74. Covariates are listed in the paper. Regressions include county and year FE, and ATT x population weights. Y-axis shows coefficients on leads and lags dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

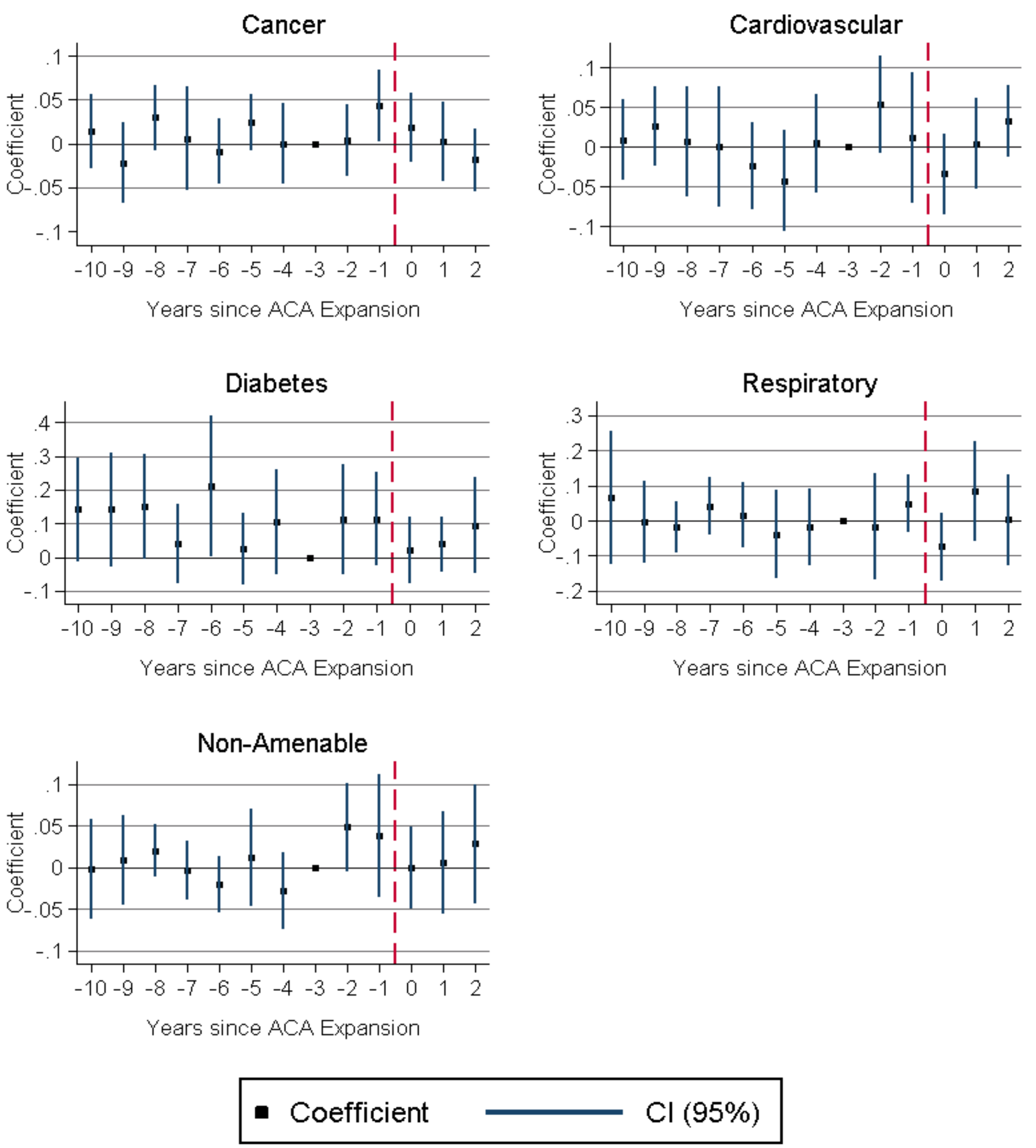
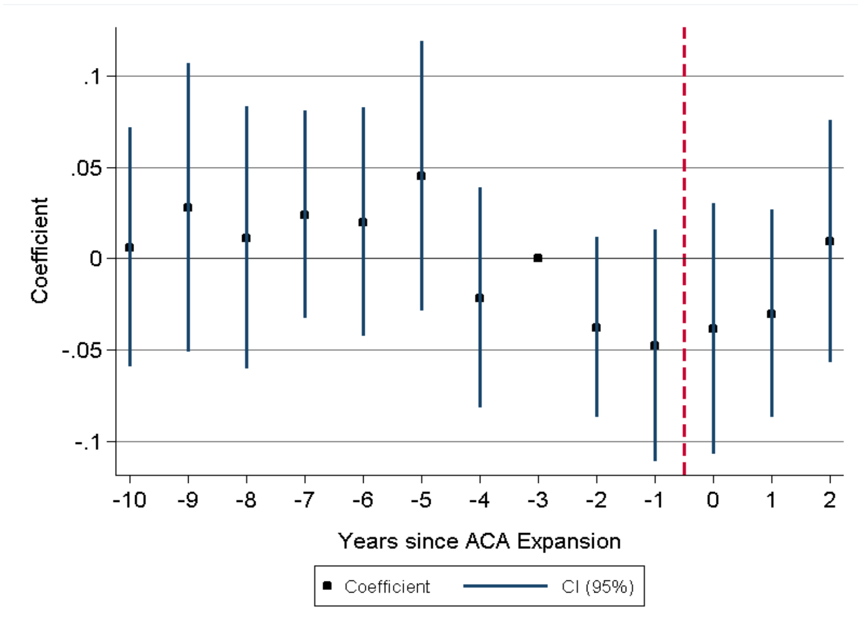


Figure A-15: Leads and Lags Graphs for High-vs-Low Uninsurance and Poverty, ATT x Pop weights

Graphs show leads and lags regressions of triple differences for high versus low uninsurance and high vs. low poverty counties, of *ln*[(amenable mortality/100,000 persons)+1] for persons aged 55-64, in Full-Expansion States versus No-Expansion States, over 2004-2016. High (low) uninsurance counties are those with highest (lowest) uninsurance rates in 2013 containing 20% of U.S. population, and similarly for high (low) poverty counties. Covariates are listed in the paper. Regressions include county and year FE, and ATT x Pop weights. Y-axis shows coefficients on lead and lag dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

Panel A. High-Uninsurance vs. Low-Uninsurance Counties



Panel B. High-Poverty vs. Low-Poverty Counties

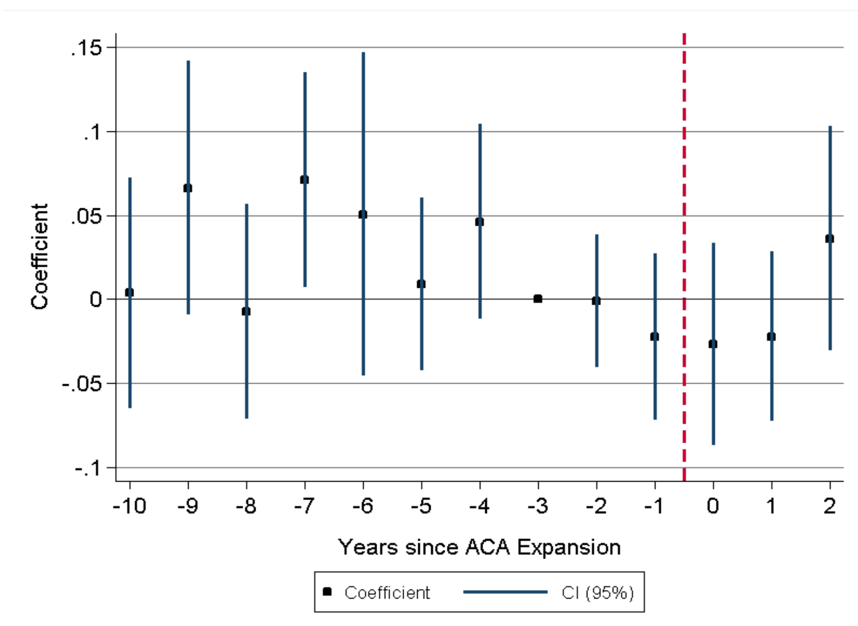
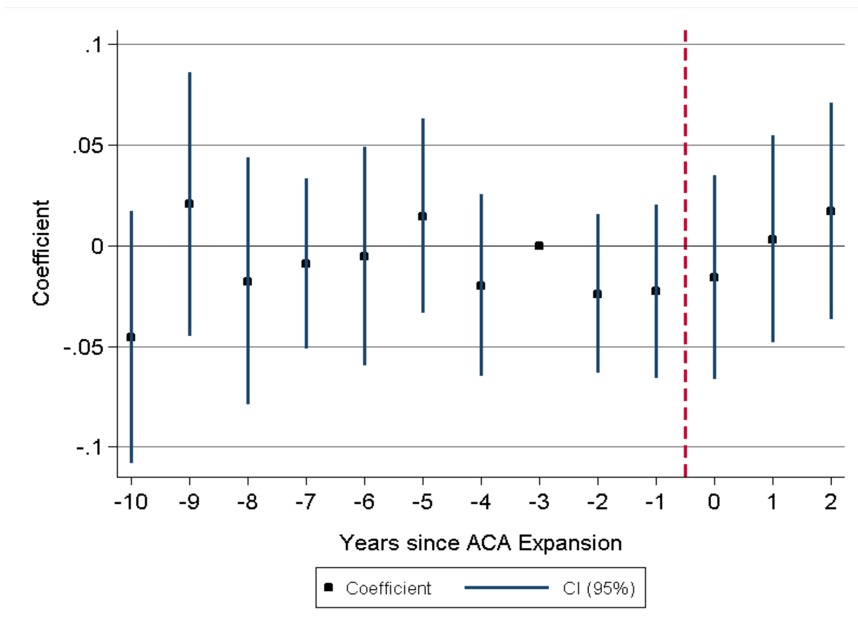


Figure A-16: Leads and Lags Graphs for High-vs-Low Uninsurance and Poverty, 18-64 years

Graphs show leads and lags regressions of triple differences for high versus low uninsurance and high vs. low poverty counties, of *ln*[(amenable mortality/100,000 persons)+1] for persons aged 18-64, in Full-Expansion States versus No-Expansion States, over 2004-2016. High (low) uninsurance counties are those with highest (lowest) uninsurance rates in 2013 containing 20% of U.S. population, and similarly for high (low) poverty counties. Covariates are listed in the paper. Regressions include county and year FE, and county population weights. Y-axis shows coefficients on lead and lag dummies; vertical bars show 95% CIs around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

Panel A. High-Uninsurance vs. Low-Uninsurance Counties



Panel B. High-Poverty vs. Low-Poverty Counties

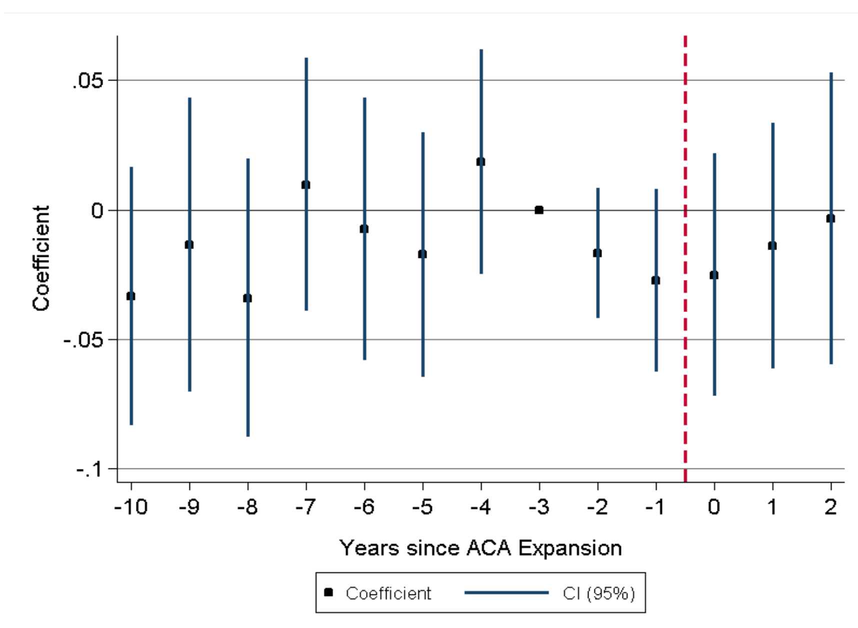


Figure A-17. DiD Leads-and-Lags Results for Ages 18-64, Amenable Mortality

Graphs from DiD leads and lags regressions of *ln*[(amenable mortality/100,000 persons)+1] for Full-Expansion States versus control group of Non-Expansion States, over 2004-2016. Covariates are listed in paper. Regressions include county and year FE, and county population weights. Y-axis shows coefficients on lead and lag dummies; vertical bars show 95% confidence intervals (CIs) around coefficients, using standard errors clustered on state. Coefficient for year -3 is set to zero. Dashed vertical line separate pre-expansion from expansion period.

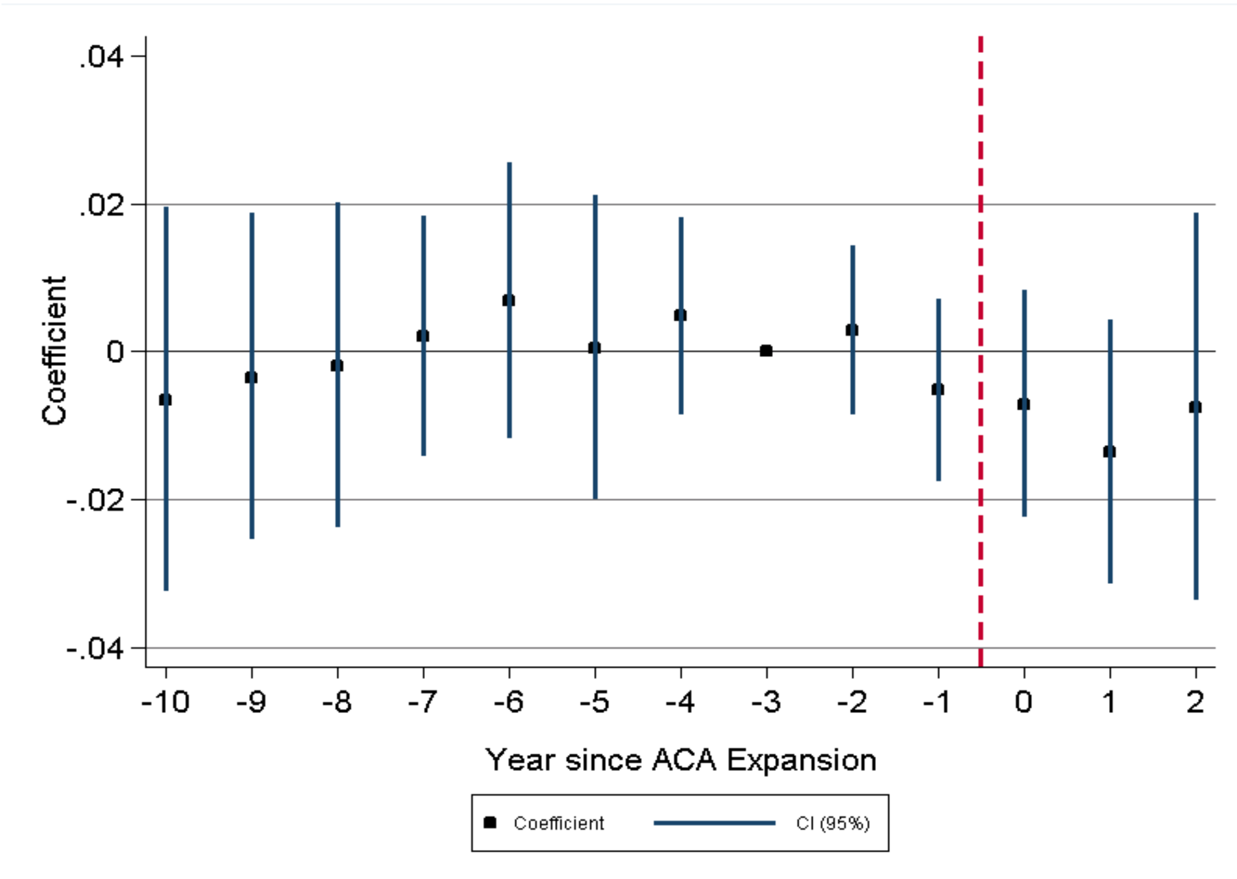
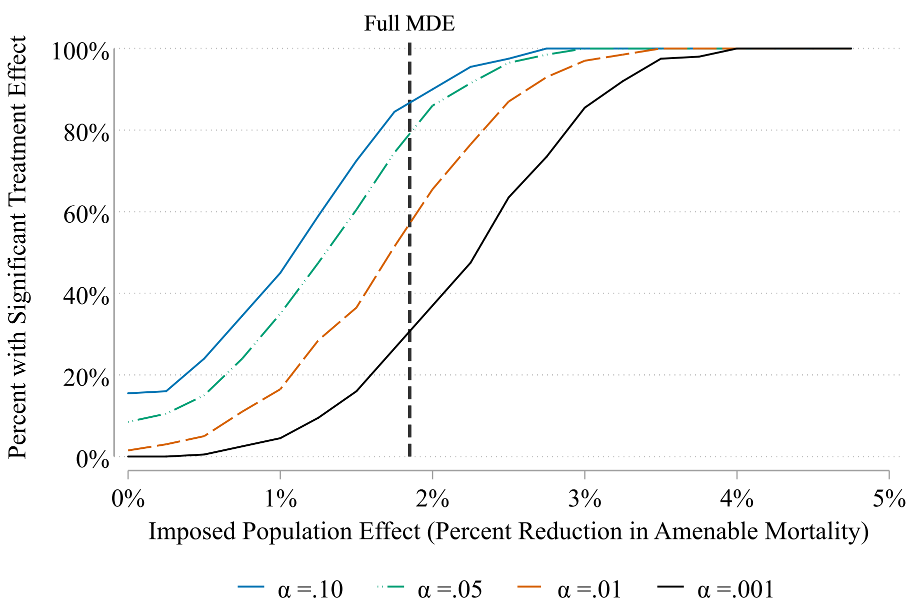


Figure A-18. Power Analyses for Full Sample: State Level DD and Triple Differences

Power curves for simulated Medicaid expansion as of January 1, 2012, applied to persons aged 55-64 during pre-treatment period (2007-2013). Graphs show power (likelihood of detecting a statistically significant effect on amenable mortality, at the indicated confidence levels, for two-tailed test), given imposed "true" population average effect. Curves are based on 1,000 replications of the DD (top graph) and triple difference (bottom graph) regression models used in Table 2, with covariates. In each draw, we select 20 pseudo-treated states at random from the combined set of 41 treated and control states, and remove a fraction of the observed deaths at random from the treated states, where the fraction reflects an imposed treatment effect (for the entire population), and we vary the imposed treatment effect from 0-5% in increments of 0.1%. Curves for α = .10/.05/.01/.001 correspond to 90%/95%/99%/99.9% confidence levels, respectively. Dashed vertical line indicates minimum detectable effect at 95% confidence level, with 80% power, for full sample (Full MDE).



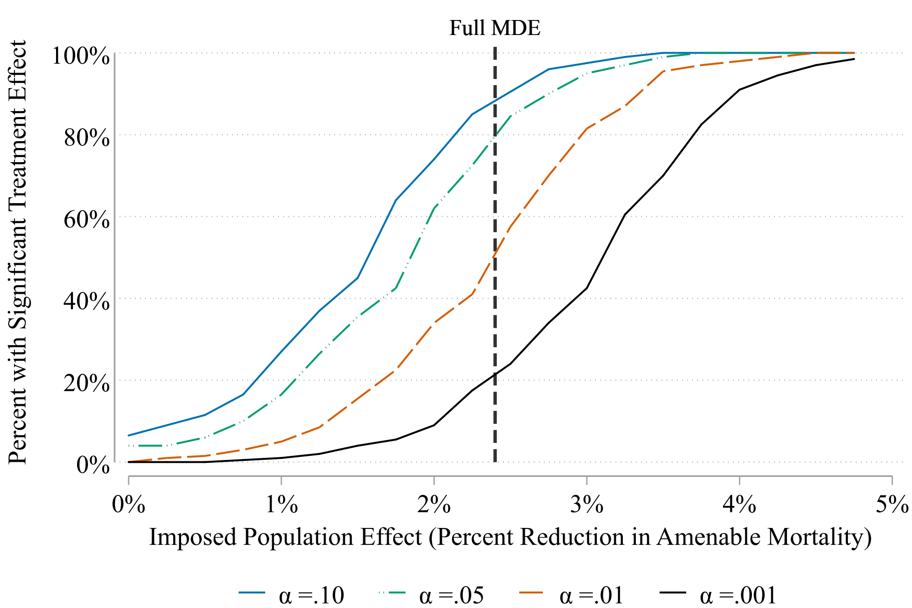
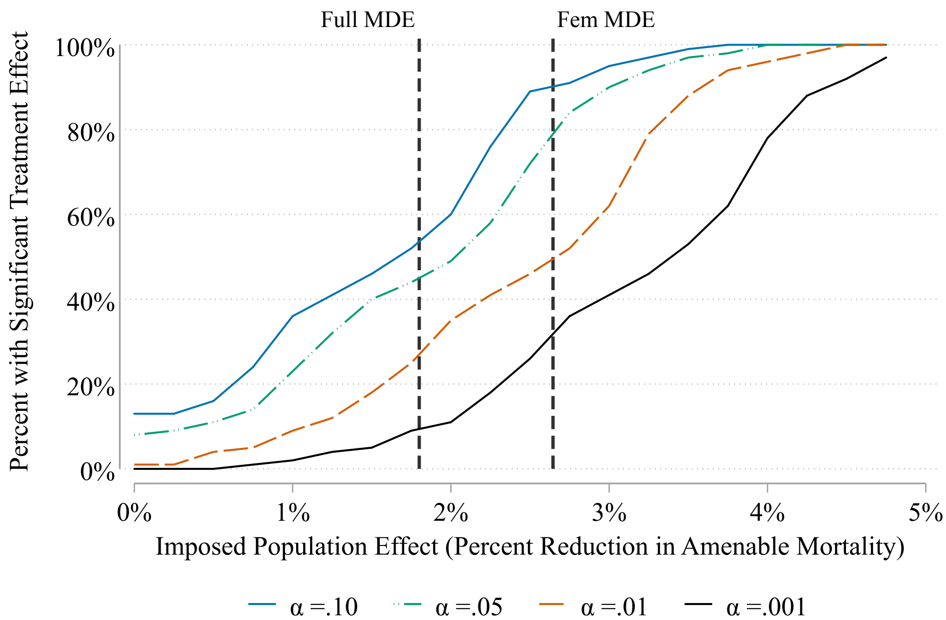


Figure A-19. Power Analysis for Women: DD and Triple Differences

Power curves for simulated Medicaid expansion as of January 1, 2012, applied to females aged 55-64 during pre-treatment period (2007-2013). Graphs show power (likelihood of detecting a statistically significant effect on amenable mortality, at the indicated confidence levels, for two-tailed test), given imposed "true" population average effect. Curves are based on 1,000 replications of the DD (top graph) and triple difference (bottom graph) regression models used in Table 2, with covariates. In each draw, we select 20 pseudo-treated states at random from the combined set of 41 treated and control states, and remove a fraction of the observed deaths at random from the treated states, where the fraction reflects an imposed treatment effect (for the entire population), and we vary the imposed treatment effect from 0-5% in increments of 0.1%. Curves for α = .10/.05/.01/.001 correspond to 90%/95%/99%/99.9% confidence levels, respectively. Dashed vertical lines indicate minimum detectable effects at 95% confidence level, with 80% power, for full sample (Full MDE) and for women (Fem MDE).



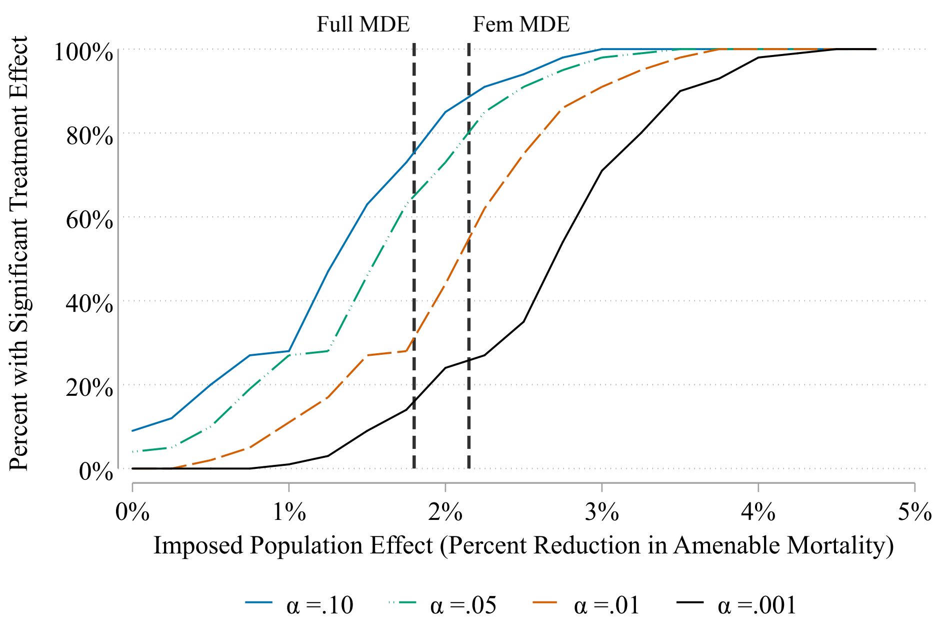
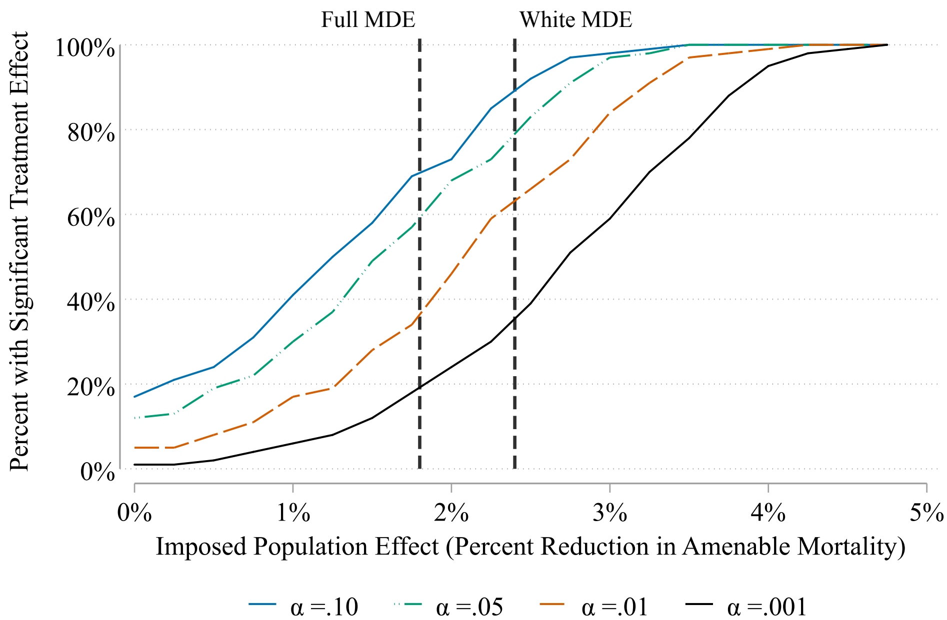


Figure A-20. Power Analysis for Non-Hispanic Whites: DD and Triple Differences

Power curves for simulated Medicaid expansion as of January 1, 2012, applied to non-Hispanic whites aged 55-64 during pre-treatment period (2007-2013). Graphs show power (likelihood of detecting a statistically significant effect on amenable mortality, at the indicated confidence levels, for two-tailed test), given imposed "true" population average effect. Curves are based on 1,000 replications of the DD (top graph) and triple difference (bottom graph) regression models used in Table 2, with covariates. In each draw, we select 20 pseudo-treated states at random from the combined set of 41 treated and control states, and remove a fraction of the observed deaths at random from the treated states, where the fraction reflects an imposed treatment effect (for the entire population), and we vary the imposed treatment effect from 0-5% in increments of 0.1%. Curves for α = .10/.05/.01/.001 correspond to 90%/95%/99%/99.9% confidence levels, respectively. Dashed vertical lines indicate minimum detectable effects at 95% confidence level, with 80% power, for full sample (Full MDE) and for non-Hispanic whites (White MDE).



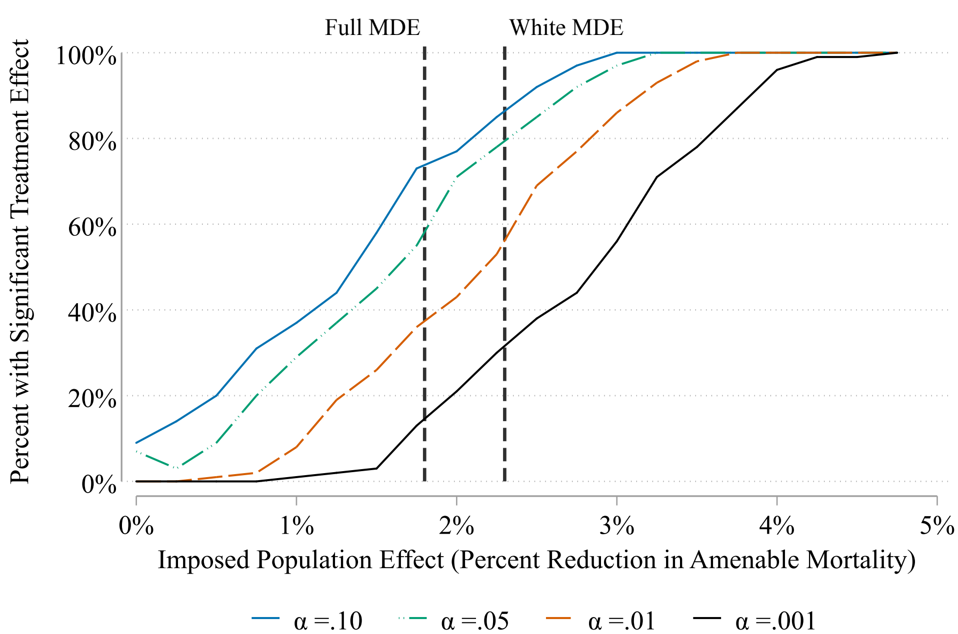
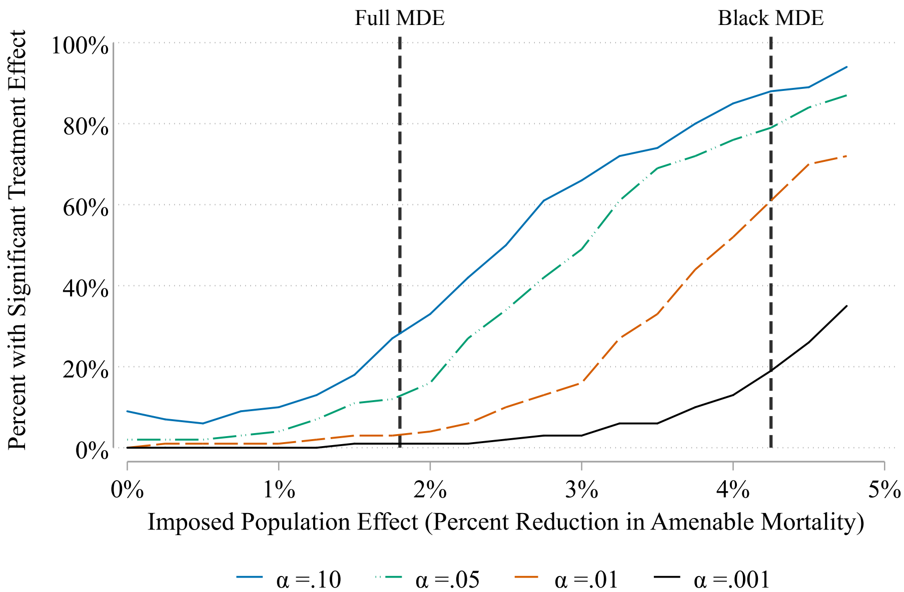


Figure A-21. Power Analysis for Non-Hispanic Blacks: DD and Triple Differences

Power curves for simulated Medicaid expansion as of January 1, 2012, applied to non-Hispanic blacks aged 55-64 during pre-treatment period (2007-2013). Graphs show power (likelihood of detecting a statistically significant effect on amenable mortality, at the indicated confidence levels, for two-tailed test), given imposed "true" population average effect. Curves are based on 1,000 replications of the DD (top graph) and triple difference (bottom graph) regression models used in Table 2, with covariates. In each draw, we select 20 pseudo-treated states at random from the combined set of 41 treated and control states, and remove a fraction of the observed deaths at random from the treated states, where the fraction reflects an imposed treatment effect (for the entire population), and we vary the imposed treatment effect from 0-5% in increments of 0.1%. Curves for α = .10/.05/.01/.001 correspond to 90%/95%/99%/99.9% confidence levels, respectively. Dashed vertical lines indicate minimum detectable effects at 95% confidence level, with 80% power, for full sample (Full MDE) and for non-Hispanic blacks (Black MDE).



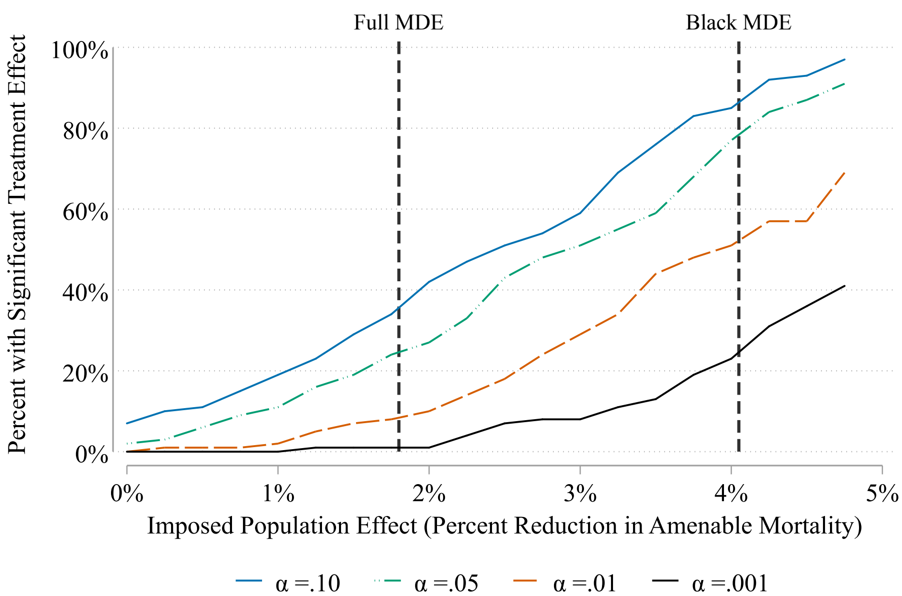
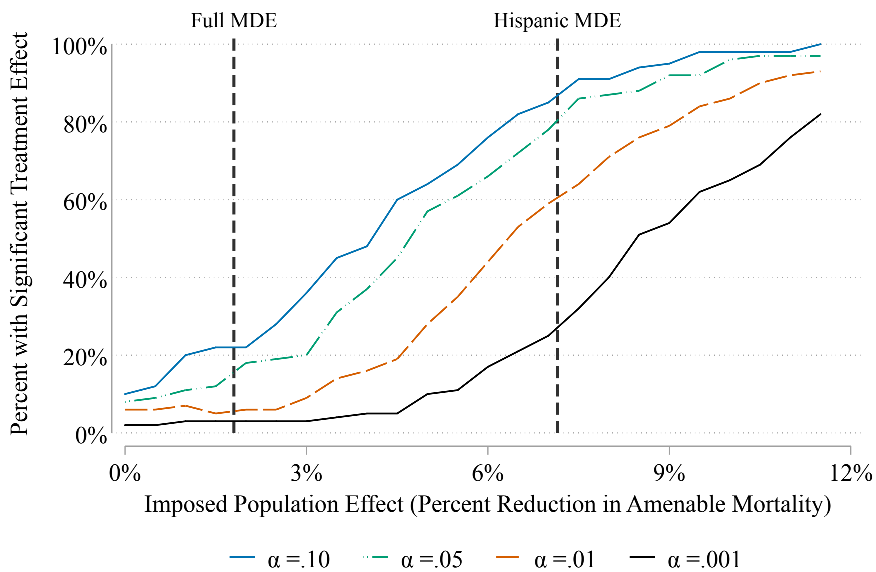


Figure A-22. Power Analysis for Hispanics: DD and Triple Differences

Power curves for simulated Medicaid expansion as of January 1, 2012, applied to non-white, non-black Hispanics aged 55-64 during pre-treatment period (2007-2013). Graphs show power (likelihood of detecting a statistically significant effect on amenable mortality, at the indicated confidence levels, for two-tailed test), given imposed "true" population average effect. Curves are based on 1,000 replications of the DD (top graph) and triple difference (bottom graph) regression models used in Table 2, with covariates. In each draw, we select 20 pseudo-treated states at random from the combined set of 41 treated and control states, and remove a fraction of the observed deaths at random from the treated states, where the fraction reflects an imposed treatment effect (for the entire population), and we vary the imposed treatment effect from 0-5% in increments of 0.1%. Curves for α = .10/.05/.01/.001 correspond to 90%/95%/99%/99.9% confidence levels, respectively. Dashed vertical line indicates minimum detectable effect at 95% confidence level, with 80% power for full sample (Full MDE) and for Hispanics (Hispanic MDE).



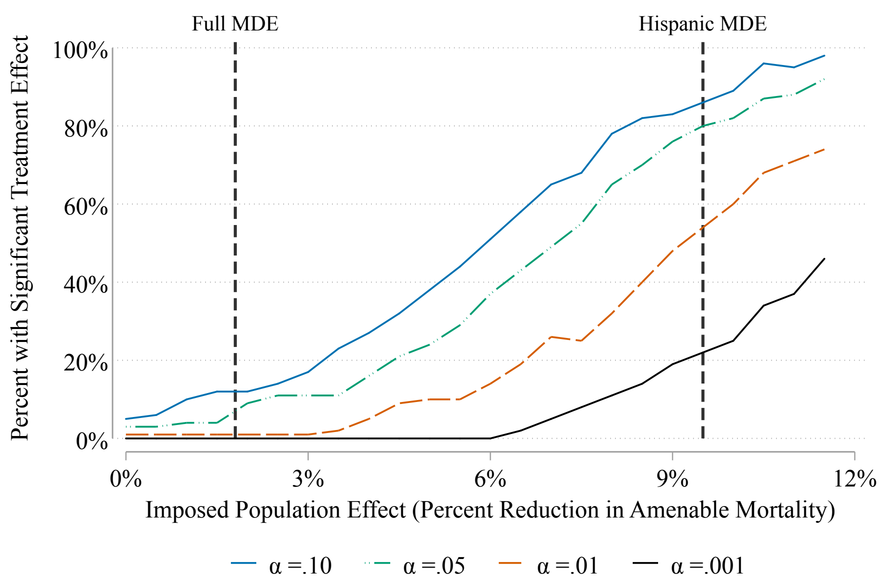


Figure A-23. Power Analysis for Low Education Subsample: DD Design

Power curves for simulated Medicaid expansion as of January 1, 2012, applied to those without a high school education aged 45-64 during pre-treatment period (2007-2013). Demographic data on education is available only for broad age groups (the best available was ages 45-64) so we present only DD and not triple difference results. Graphs show power (likelihood of detecting a statistically significant effect on amenable mortality, at the indicated confidence levels, for two-tailed test), given imposed "true" population average effect. Curves are based on 1,000 replications of the DD regression model used in Table 2, with covariates. In each draw, we select 20 pseudo-treated states at random from the combined set of 41 treated and control states, and remove a fraction of the observed deaths at random from the treated states, where the fraction reflects an imposed treatment effect (for the entire population), and we vary the imposed treatment effect from 0-5% in increments of 0.1%. Curves for α = .10/.05/.01/.001 correspond to 90%/95%/99%/99.9% confidence levels, respectively. Dashed vertical lines indicates minimum detectable effect at 95% confidence level, with 80% power for full sample (Full MDE) and for low-education subsample (Low Educ. MDE).

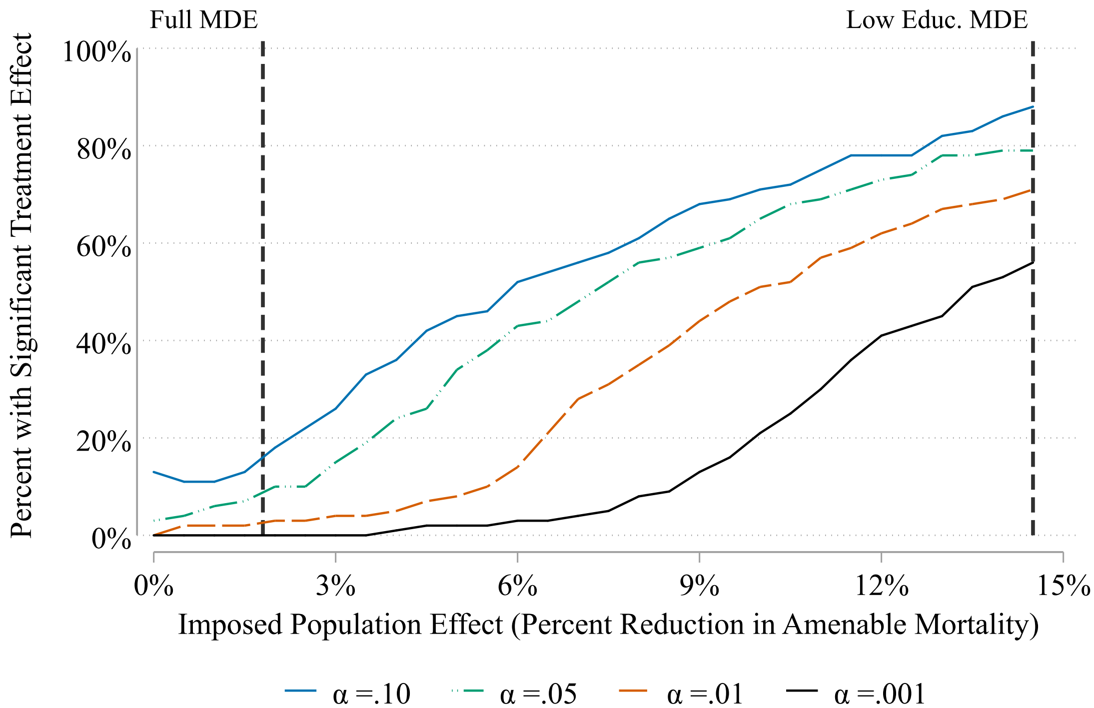


Figure A-24. Uninsurance Rate by Single Year of Age

Source: Authors' calculations from American Community Survey 2009, 2013 and 2015

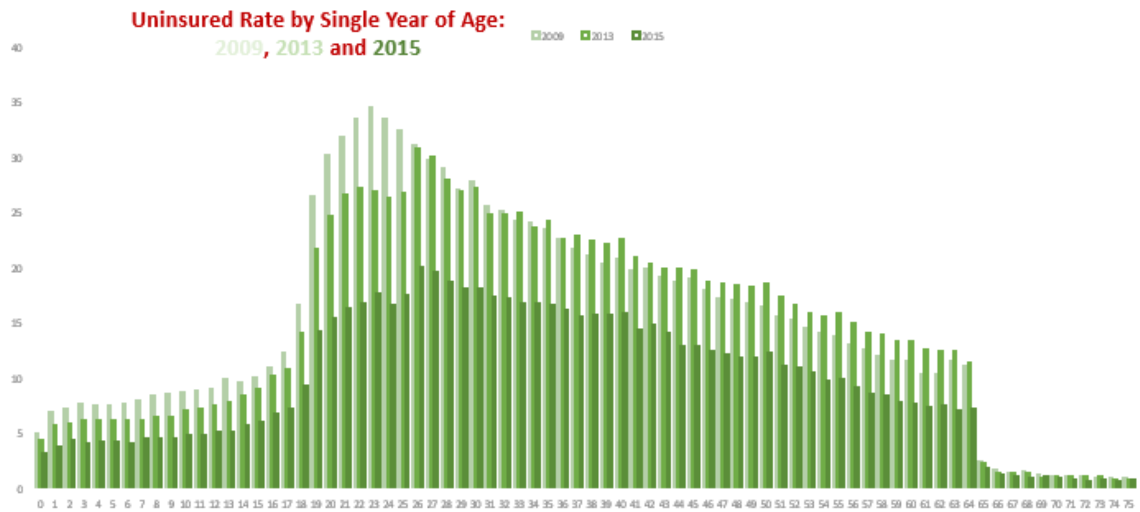


Figure A-25. Difference in Uninsurance Rate from 2012 to 2016 by Expansion Status

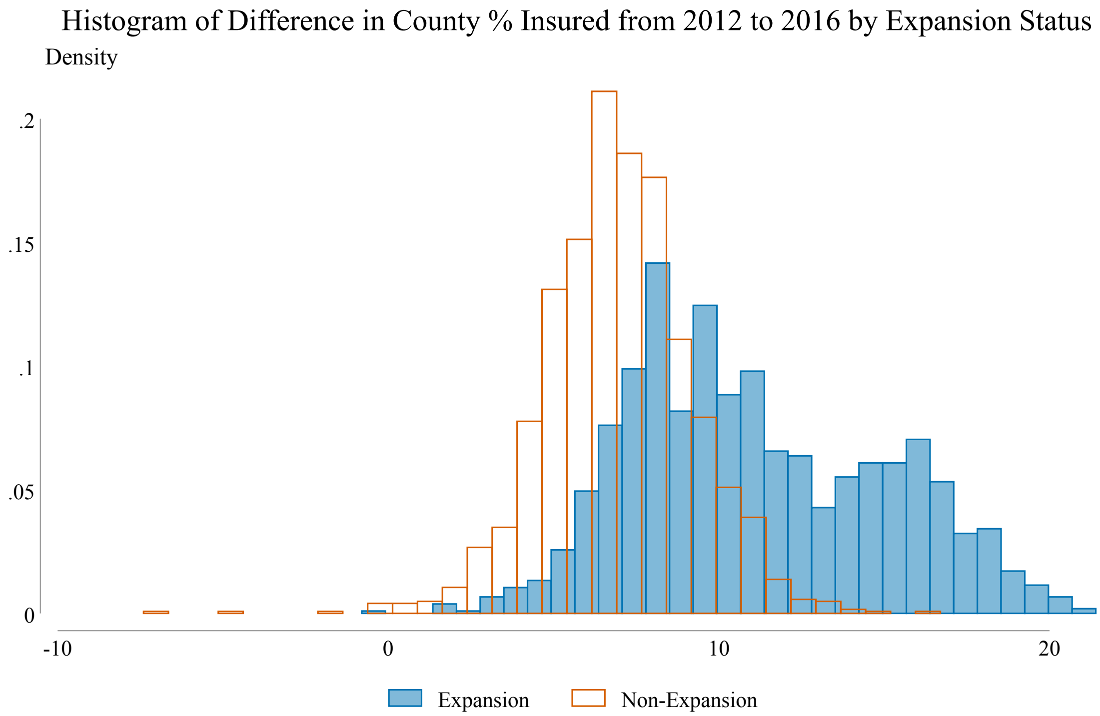
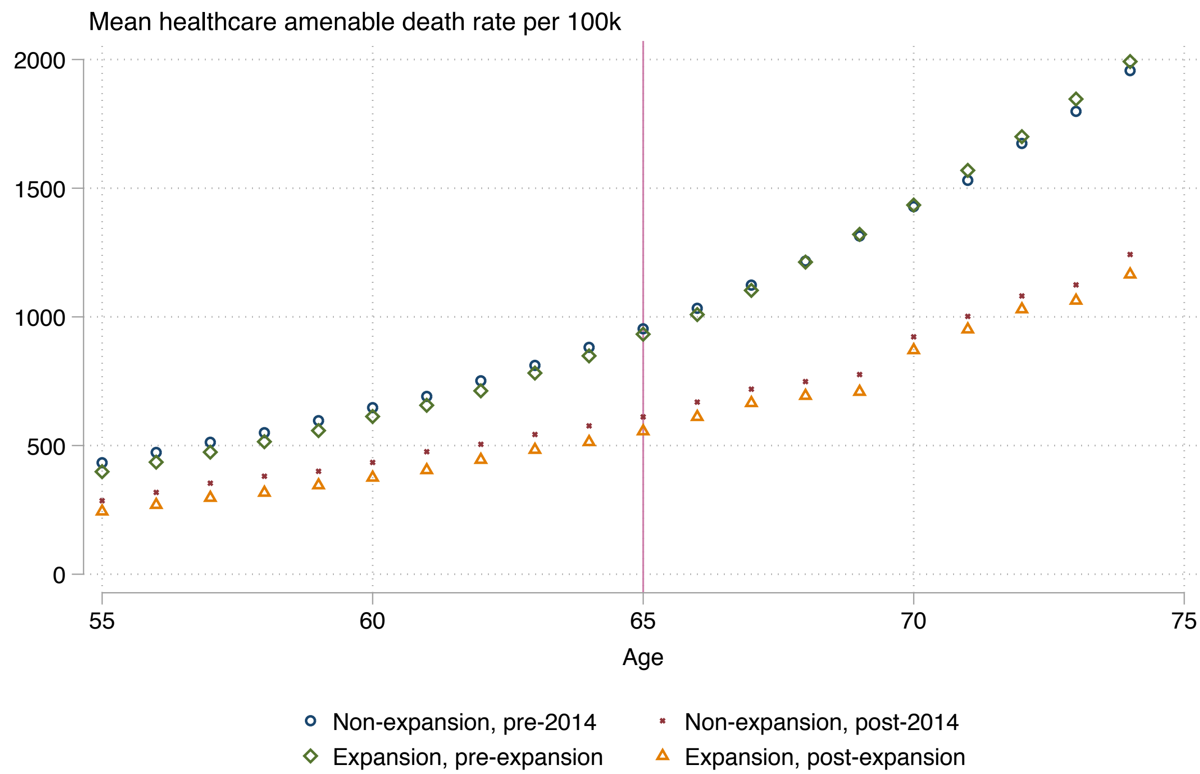


Figure A-26. Changes in mortality by single year of age

Mean health care amenable death rate per 100,000 by single year of age are reported for both expansion and non-expansion states before and after expansion. Difference across time (pre-2014 to post-2014 for non-expansion states; and pre-expansion to post-expansion in expansion states) illustrate that the death rate of each single year of age in expansion states have reduced relative to each analogous group in non-expansion states. The differences across age groups (55-64 v 65-74) illustrate that this improvement was not limited to those eligible for Medicaid. That is, the improvement occurred for Medicare enrollees as well. Thus even with disaggregated data by age, we do not find conclusive evidence of a Medicaid expansion impact on the mortality rate for the near elderly (55-64).

Source: Author calculations from restricted access mortality files.



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Example Simulated Power Analysis from Black, Hollingsworth, Nunes, and Simon (2019)

Alex Hollingsworth

3 January 2019

This is an example of the type of simulated power analysis done in Black et al. (2019). This example is done with publicly available data. You can find the code, data, and output for this example hosted on Alex's GitHub page https://github.com/hollina/health_insurance_and_mortality.

This set-up is designed to mimic a typical DiD setting. Here we will compare 23 randomly chosen treated states to 18 randomly chosen control states. We will impose a series of treatment effects that gradually increase in magnitude and report whether or not these imposed treatment effects are detectable. We will vary the set of randomly chosen treated states. We will calculate the minimum detectable effect size at various power and significance levels. We will also explore a measure of believability, which is based upon Gelman and Carlin (2014) measures of sign and magnitude error.

In this simple design we used 5 years of pre-expansion data and 3 years of post-expansion data. Both state and year fixed-effects are included. Regressions are weighted by state-population and standard errors will be clustered at the state-level. The dependent variable will be the natural log of the all-cause non-elderly mortality rate per 100,000.

This code is simply an example of our simulated power analysis and is not an attempt to identify the impact of Medicaid expansion on mortality. Importantly, changing the research design (e.g. adding control variables, shifting to the county-level, changing the cause of death, using propensity score weights, or using a synthetic control estimator) will impact power. Our approach could be easily modified to accommodate any of these alternative research designs. Any improvements to the research design will very likely increase power and decrease the minimum detectable effect size.

Initial Set-up

Here we will set-up the power analysis and choose various required parameters/options.

First we clear the memory

```
. clear all
```

Choose the number of datasets we want to compose each estimate. For example, if we choose 2, then two sets of psuedo-treated states will be drawn and the power analysis will be conducted twice for each effect size; once for each set of pseudo-treated states and effect size pair.

```
. local max_dataset_number  = 1000
```

Pick the number of psuedo-post-expansion years

```
. local number_post_years = 3

. local last_year = 2013-`number_post_years'+1
```

Set number of psuedo-pre-expansion years

```
. local number_pre_years = 5

. local first_year = `last_year'-`number_pre_years'
```

Set effect size step and max value in percent terms (0-1)

```
. local step_size = .0025 // Quarter of a percent

. local end_value = .05 // End at 5%
```

Create a local macro from the choices above

```
. local step_macro

. forvalues x = 0(`step_size')`end_value' {
  2.     local step_macro `step_macro'  `x'
  3. }
```

Determine the length of the macro above, so percent complete can be displayed later

```
. local num :  word count `step_macro'

. local num = `num'
```

Calculate the max number of rows so percent complete can be displayed later

```
. local max_row = `max_dataset_number'*`num'
```

Create excel sheet to store results from simulation. Note: I have $dropbox set via my profile.do to point to my Dropbox folder.

```
. putexcel set
"$dropbox/health_insurance_and_mortality/state_level_public_dat
> a_example/output/power_simulation_results.xlsx", replace
```

Initialize cells names in excel sheet

```
. putexcel A1 = ("dependent_variable")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
```

```
> _data_example/output/power_simulation_results.xlsx saved

. putexcel B1 = ("controls")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved

. putexcel C1 = ("weight")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved

. putexcel D1 = ("treated_states")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved

. putexcel E1 = ("effect_size")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved
. putexcel F1 = ("deaths_reduced_per_year")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved

. putexcel G1 = ("total_deaths_reduced")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved
. putexcel H1 = ("coef")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved

. putexcel I1 = ("se")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved

. putexcel J1 = ("df")
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/output/power_simulation_results.xlsx saved
```

Import and clean mortality data

Import data extracted from CDC wonder. All cause mortality 0-64 by state and year. The data were gathered on 1 January 2019.

```
. import delimited
"$dropbox/health_insurance_and_mortality/state_level_public
> _data_example/data/Multiple Cause of Death, 1999-2017.txt"
(8 vars, 1,077 obs)
```

Drop total variables

```
. drop if missing(year)
(108 observations deleted)
```

Drop unneeded variables from CDC Wonder

```
. drop notes
```

Drop years after expansion

```
. drop if year>=2014
(204 observations deleted)
```

Drop if year before first desired year

```
. drop if year<`first_year'
(357 observations deleted)
```

Change state name to be state postal code

```
. replace state ="AL" if state=="Alabama"
(8 real changes made)

. replace state ="AK" if state=="Alaska"
(8 real changes made)

. replace state ="AZ" if state=="Arizona"
(8 real changes made)

. replace state ="AR" if state=="Arkansas"
(8 real changes made)

. replace state ="CA" if state=="California"
(8 real changes made)

. replace state ="CO" if state=="Colorado"
(8 real changes made)

. replace state ="CT" if state=="Connecticu "
(0 real changes made)

. replace state ="DE" if state=="Delaware"
(8 real changes made)

. replace state ="DC" if state=="District of Columbia"
(8 real changes made)

. replace state ="FL" if state=="Florida"
(8 real changes made)

. replace state ="GA" if state=="Georgia"
(8 real changes made)

. replace state ="HI" if state=="Hawaii"
(8 real changes made)
```

```
. replace state ="ID" if state=="Idaho"
(8 real changes made)

. replace state ="IL" if state=="Illinois"
(8 real changes made)

. replace state ="IN" if state=="Indiana"
(8 real changes made)

. replace state ="IA" if state=="Iowa"
(8 real changes made)

. replace state ="KS" if state=="Kansas"
(8 real changes made)

. replace state ="KY" if state=="Kentucky"
(8 real changes made)

. replace state ="LA" if state=="Louisiana"
(8 real changes made)

. replace state ="ME" if state=="Maine"
(8 real changes made)

. replace state ="MD" if state=="Maryland"
(8 real changes made)

. replace state ="MA" if state=="Massachusetts"
(8 real changes made)

. replace state ="MI" if state=="Michigan"
(8 real changes made)

. replace state ="MN" if state=="Minnesota"
(8 real changes made)

. replace state ="MS" if state=="Mississippi"
(8 real changes made)

. replace state ="MO" if state=="Missouri"
(8 real changes made)

. replace state ="MT" if state=="Montana"
(8 real changes made)

. replace state ="NE" if state=="Nebraska"
(8 real changes made)

. replace state ="NV" if state=="Nevada"
(8 real changes made)

. replace state ="NH" if state=="New Hampshire"
(8 real changes made)

. replace state ="NJ" if state=="New Jersey"
(8 real changes made)

. replace state ="NM" if state=="New Mexico"
(8 real changes made)

. replace state ="NY" if state=="New York"
(8 real changes made)
```

```
. replace state ="NC" if state=="North Carolina"
(8 real changes made)

. replace state ="ND" if state=="North Dakota"
(8 real changes made)

. replace state ="OH" if state=="Ohio"
(8 real changes made)

. replace state ="OK" if state=="Oklahoma"
(8 real changes made)

. replace state ="OR" if state=="Oregon"
(8 real changes made)

. replace state ="PA" if state=="Pennsylvania"
(8 real changes made)

. replace state ="RI" if state=="Rhode Island"
(8 real changes made)

. replace state ="SC" if state=="South Carolina"
(8 real changes made)

. replace state ="SD" if state=="South Dakota"
(8 real changes made)

. replace state ="TN" if state=="Tennessee"
(8 real changes made)

. replace state ="TX" if state=="Texas"
(8 real changes made)

. replace state ="UT" if state=="Utah"
(8 real changes made)

. replace state ="VT" if state=="Vermont"
(8 real changes made)

. replace state ="VA" if state=="Virginia"
(8 real changes made)

. replace state ="WA" if state=="Washington"
(8 real changes made)

. replace state ="WV" if state=="West Virginia"
(8 real changes made)

. replace state ="WI" if state=="Wisconsin"
(8 real changes made)

. replace state ="WY" if state=="Wyoming"
(8 real changes made)
```

Add expansion status to each state

```
. gen expansion4=0

. label define expansion4 0 "0. Non-expansion" 1 "1. Full expansion" ///
>     2 "2. Mild expansion" 3 "3. Substantial expansion"

. label values expansion4 expansion4
```

```
. local full AZ AR CO IL IA KY MD NV NM NJ ND OH OR RI WV  WA

. foreach x in `full' {
  2.     replace expansion4=1 if state=="`x'"
  3. }
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)

. local mild DE DC MA NY VT

. foreach x in `mild' {
  2.     replace expansion4=2 if state=="`x'"
  3. }
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)

. local medium CA CT HI MN WI

. foreach x in `medium' {
  2.     replace expansion4=3 if state=="`x'"
  3. }
(8 real changes made)
(0 real changes made)
(8 real changes made)
(8 real changes made)
(8 real changes made)
```

Account for mid-year expansions

```
. replace expansion4=1 if state=="MI"  //MI expanded in April 2014
(8 real changes made)

. replace expansion4=1 if state=="NH"  //NH expanded in August 2014
(8 real changes made)

. replace expansion4=1 if state=="PA"  //PA expanded in Jan 2015
(8 real changes made)

. replace expansion4=1 if state=="IN"  //IN expanded in Feb 2015
(8 real changes made)

. replace expansion4=1 if state=="AK"  //AK expanded in Sept 2015
(8 real changes made)

. replace expansion4=1 if state=="MT"  //MT expanded in Jan 2016
```

```
(8 real changes made)

. replace expansion4=1 if state=="LA"  //LA expanded in July 2016
(8 real changes made)
```

Keep only full or non-expansion states

```
. drop if expansion4==2 | expansion4==3
(72 observations deleted)
```

Store number of expansion states

```
. distinct statecode  if expansion4==1

             |        Observations
             |      total   distinct
-------------+----------------------
   statecode |        184         23

. scalar number_expand = r(ndistinct)
```

Save data to be called in power analysis

Save temporary dataset to be called

```
. compress
  variable expansion4 was float now byte
  variable population was double now long
  variable state was str20 now str11
  (5,376 bytes saved)

. save
"$dropbox/health_insurance_and_mortality/state_level_public_data_exampl
> e/temp/temp_data.dta", replace
(note: file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level
> _public_data_example/temp/temp_data.dta not found)
file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_public
> _data_example/temp/temp_data.dta saved
```

Run simulated power analysis

Start a timer to show how long this takes

```
. timer on 1
```

Set row number for excel sheet

```
. local row =2
```

Run a loop. Performing the power analysis once for each of the desired number of datasets. The following output is supressed for the html document even though it runs. This is to ensure the document is not too long.

```
. forvalues dataset_number = 1(1)`max_dataset_number'    {
  2.     // Display the dataset number
.     qui di "`dataset_number'"
.     // Open main dataset for analysis
.     qui use
"$dropbox/health_insurance_and_mortality/state_level_public_data
> _example/temp/temp_data.dta", clear
.     // Set seed for reproducibility. We want the seed to be the same within
> a dataset.
.     qui local rand_seed = 1234 + `dataset_number'
  5.     qui set seed   `rand_seed'
.
///////////////////////////////////////////////////////////////////////
> ///////
>     // Generate a random variable for each state, then the first N in rank
w
> ill be
.     // considered expansion states. Where N is # of expansion states
.     qui bysort statecode: gen random_variable = runiform() if _n==1
  7.     qui bysort statecode: carryforward random_variable, replace
.     // Rank the states
.     qui egen rank = group(random_variable)
.     // Given this random ordering of states, assign expansion status to the
> # set above
.     qui gen expansion = 0
 10.     qui replace expansion=1 if rank <=number_expand
.     // Do this same thing for the treatment variable
.     qui gen treatment = 0
 12.     qui replace treatment = 1 if expansion==1 & year>=`last_year'
.     // Create Post variable
.     qui gen post = 0
 14.     qui replace post =1 if year>=`last_year'
.     // Store basic data from regression in excel sheet
.     qui putexcel A`row' = ("all_deaths")
 16.     qui putexcel B`row' = ("no controls")
 17.     qui putexcel C`row' = ("population")
.     // Add list of states to excel sheet
.     qui capture drop test
 19.     qui gen test = ""
.     qui levelsof state if treatment ==1, local(treated_states)
 21.     foreach x in `treated_states' {
 22.         qui replace test = test + ", " + "`x'"
 23.     }
.     qui local state_list `=test[1]'
 25.     qui putexcel D`row' = ("`state_list'")
.     // Generate a death rate with no effect
.     qui gen death_rate = (deaths/population)*100000
.     // Gen order variable
.     qui gen order = _n
.
///////////////////////////////////////////////////////////////////////
> /////
>     // Create a reduced deaths variable by a given percentage using the
bino
> mial for each effect size
```

```
.     qui local counter = 1
.     foreach x in `step_macro' {
 30.         qui gen reduced_deaths_`counter' = 0
 31.         qui replace reduced_deaths_`counter' = rbinomial(deaths,`x') if
t
> reatment==1
 32.         qui replace reduced_deaths_`counter'=0 if
missing(reduced_deaths_
> `counter')
.         qui gen deaths_`counter' = deaths - reduced_deaths_`counter'
 34.         qui replace deaths_`counter'=0 if missing(deaths_`counter')
.         qui gen death_rate_`counter'=
ln((deaths_`counter'/population)*10000
> 0+1)
.         // Store the effect size in excel sheet
.         qui putexcel E`row' = (`x')
.         // Store the number of reduced deaths in excel sheet
.         qui sum reduced_deaths_`counter' if year>=`last_year'
 38.         qui putexcel F`row' = (`r(sum)'/`number_post_years')
 39.         qui putexcel G`row' = (`r(sum)')
.         // Move the row and counter one forward
.         qui local counter = `counter' + 1
 41.         qui local row = `row' + 1
 42.     }
.     // Move the row counter back to the top
.     qui local row = `row' - `num'
.
////////////////////////////////////////////////////////////////////////
> /////
>     // Run regression of treatment on reduced deaths variable for each
effec
> t size
.     // Reset the counter
.     qui local counter = 1
.     forvalues counter = 1(1)`num' {
.         qui reghdfe death_rate_`counter' ///
>             treatment ///
>             i.post i.expansion ///
>             [aweight=population] ///
>             ,  absorb(statecode year)  vce(cluster statecode)
.         // Store results
.         qui putexcel H`row' =(_b[treatment])
 48.         qui putexcel I`row' = (_se[treatment])
 49.         qui putexcel J`row' =(`e(df_r)')
.         // Display Percent Complete
.         qui di
"////////////////////////////////////////////////////////////
> //////////"
 51.         qui di "///////////////////////////Percent
Complete/////////////
> /////////////"
 52.         qui di ((`row'-1)/`max_row')*100
 53.         qui di
"/////////////////////////////////////////////////////////
> //////////////"
.         qui local row = `row' + 1
 55.         qui local counter = `counter' + 1
 56.     }
 57. }
```

Stop timer

```
. timer off 1

. timer list
   1:  79905.50 /        1 =   79905.5020
```

Erase temporary dataset used for analysis

```
. erase
"$dropbox/health_insurance_and_mortality/state_level_public_data_examp
> le/temp/temp_data.dta"
```

Import and clean results from simulated power analysis

Import simulation results

```
. import excel
"$dropbox/health_insurance_and_mortality/state_level_public_dat
> a_example/output/power_simulation_results.xlsx", sheet("Sheet1") firstrow
cl
> ear
```

Calculate z-scores and p-values

```
. gen z_score = abs(((coef - 0)/se))

. gen p_value =  2*ttail(df,z_score)
```

Calculate indicator for power threshold for each observation

```
. gen power_10 = 0

. gen power_05 = 0

. gen power_01 = 0

. gen power_001 = 0
. replace power_10 =  1 if p_value<= .1
(12,536 real changes made)

. replace power_05 =  1 if p_value<= .05
(11,065 real changes made)

. replace power_01 =  1 if p_value<= .01
(8,209 real changes made)

. replace power_001 = 1 if p_value<= .001
(4,872 real changes made)
```

Calculate a count variable

```
. gen count = 1
```

Make sign error

```
. gen s_error_10 = 0

. replace s_error_10 =1 if power_10==1 & coef>=0
(174 real changes made)

. gen s_error_05 = 0

. replace s_error_05 =1 if power_05==1 & coef>=0
(85 real changes made)

. gen s_error_01 = 0

. replace s_error_01 =1 if power_01==1 & coef>=0
(17 real changes made)

. gen s_error_001 = 0

. replace s_error_001 =1 if power_001==1 & coef>=0
(0 real changes made)
. replace s_error_10 =. if effect_size==0
(1,000 real changes made, 1,000 to missing)

. replace s_error_05 =. if effect_size==0
(1,000 real changes made, 1,000 to missing)

. replace s_error_01 =. if effect_size==0
(1,000 real changes made, 1,000 to missing)

. replace s_error_001 =. if effect_size==0
(1,000 real changes made, 1,000 to missing)
```

Make magnitude error

```
. gen m_error = abs(coef/effect_size)
(1,000 missing values generated)

. gen m_error_10 = m_error
(1,000 missing values generated)

. replace m_error_10 = . if power_10==0
(6,628 real changes made, 6,628 to missing)

. gen m_error_05 = m_error
(1,000 missing values generated)

. replace m_error_05 = . if power_05==0
(8,030 real changes made, 8,030 to missing)

. gen m_error_01 = m_error
(1,000 missing values generated)

. replace m_error_01 = . if power_01==0
```

```
(10,820 real changes made, 10,820 to missing)

. gen m_error_001 = m_error
(1,000 missing values generated)

. replace m_error_001 = . if power_001==0
(14,130 real changes made, 14,130 to missing)
```

Generate Beliveabilitiy

```
. gen believe_10 = 0

. replace  believe_10 = 1 if power_10 ==1 & s_error_10==0 & m_error_10<=2
(11,081 real changes made)
. gen believe_05 = 0

. replace  believe_05 = 1 if power_05 ==1 & s_error_05==0 & m_error_05<=2
(9,934 real changes made)
. gen believe_01 = 0

. replace  believe_01 = 1 if power_01 ==1 & s_error_01==0 & m_error_01<=2
(7,502 real changes made)
. gen believe_001 = 0

. replace  believe_001 = 1 if power_001 ==1 & s_error_001==0 & m_error_001<=2
(4,519 real changes made)
```

Collapse by effect size to calculate power, % sign error, average magnitude error and % believable

```
. collapse (sum) count *power_* *s_error_* *believe_* (mean) *m_error_*,
by(ef
> fect_size)
```

Generate sign error ratio, rather than raw count

```
. replace s_error_10 = (s_error_10/power_10)*100
(5 real changes made)

. replace s_error_05 = (s_error_05/power_05)*100
(4 real changes made)

. replace s_error_01 = (s_error_01/power_01)*100
(2 real changes made)

. replace s_error_001 = (s_error_001/power_001)*100
(0 real changes made)
. replace s_error_10 = . if effect_size==0
(1 real change made, 1 to missing)

. replace s_error_05 = . if effect_size==0
(1 real change made, 1 to missing)

. replace s_error_01 = . if effect_size==0
(1 real change made, 1 to missing)

. replace s_error_001 = . if effect_size==0
```

```
(1 real change made, 1 to missing)
```

Make power and believability out of 100

```
. ds *power* *believe_*
power_10      power_01      believe_10    believe_01
power_05      power_001     believe_05    believe_001

. foreach x in `r(varlist)' {
  2.      replace `x' = (`x'/count)*100
  3. }
(20 real changes made)
(20 real changes made)
(20 real changes made)
(20 real changes made)
(16 real changes made)
(15 real changes made)
(14 real changes made)
(13 real changes made)
```

Make effect size 0-100

```
. replace effect_size=effect_size*100
(19 real changes made)
```

Plot power curves

First determine closest point where the power_05 hits 80%

```
. gen distance_from_80 = (power_05-80)^2

. sort distance_from_80

. sum effect_size in 1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
 effect_size |          1           3           .          3          3

. local mde=`r(mean)'
```

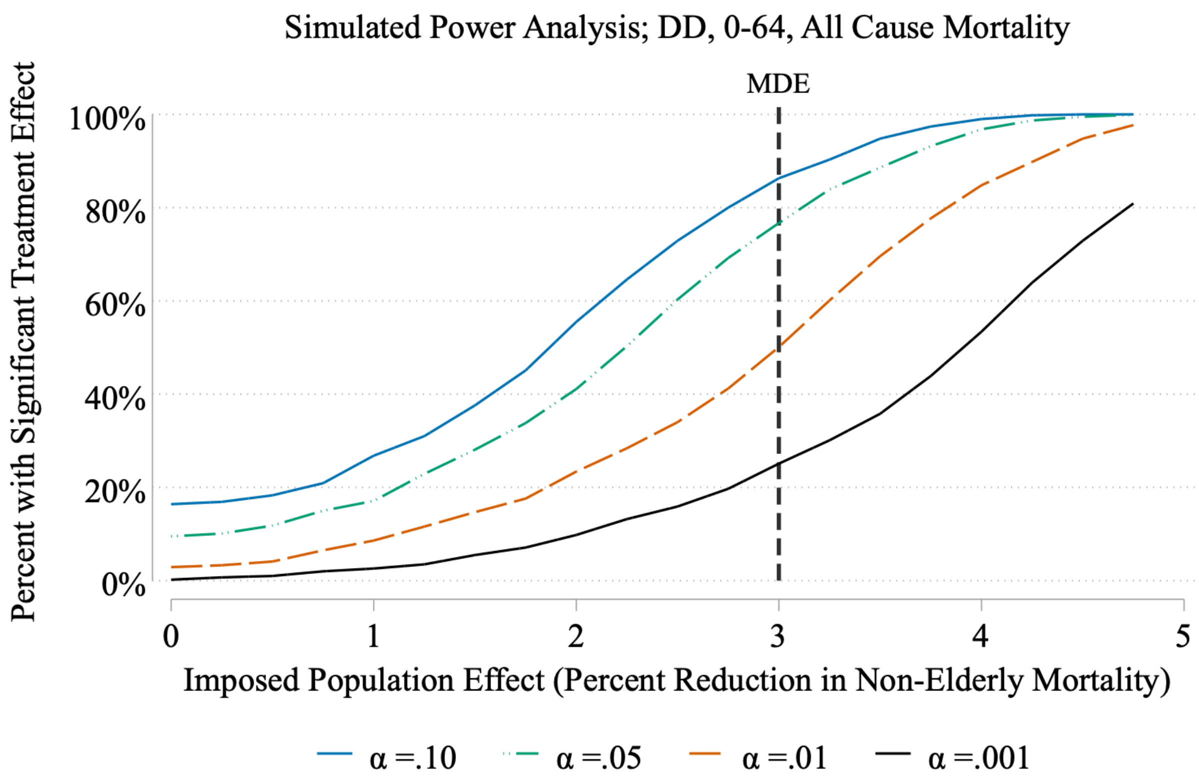
Add label to graph with this MDE

```
. capture drop mde_label

. gen mde_label = ""
(20 missing values generated)

. set obs `=_N+1'
number of observations (_N) was 20, now 21

. replace mde_label = "MDE" in `=_N'
variable mde_label was str1 now str3
```

```
(1 real change made)

. replace effect_size = `mde' in `=_N'
(1 real change made)
. capture drop full_power

. gen full_power = 102.5
```

Plot power curve

```
. sort effect_size

. twoway connected power_10 effect_size ,  lpattern("l") color(sea)
msymbol(no
> ne) mlabcolor(sea) mlabel("") mlabsize(3) mlabpos(11) ///
>     || connected  power_05 effect_size ,  lpattern(".._") color(turquoise)
m
> symbol(none) mlabcolor(turquoise) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected  power_01 effect_size , lpattern("_") color(vermillion)
msy
> mbol(none) mlabcolor(vermillion) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected  power_001  effect_size ,  lpattern("l") color(black)
msymb
> ol(none) mlabcolor(black) mlabel("") mlabsize(3) mlabpos(3) ///
>     || scatter full_power effect_size , mlabel(mde_label) msymbol(none)
mlab
> pos(12) mlabsize(3.5) ///
>         xline(`mde', lpattern(dash) lcolor(gs3) lwidth(.5) noextend) ///
>         ytitle("Percent with Significant Treatment Effect", size(4)) ///
>         xtitle("Imposed Population Effect (Percent Reduction in Non-Elderly
> Mortality)", size(4) ) ///
>         xscale(r(0 5)) ///
>         xlabel(, nogrid labsize(4)) ///
>         ylabel(0 "0%" 20 "20%"  40 "40%" 60 "60%" 80 "80%" 100 "100%",gmax
n
> oticks labsize(4)) ///
>         legend(order( 1 2 3 4) pos(6) col(4) ///
>             label(1 "{&alpha} =.10") label(2 "{&alpha} =.05") ///
>             label(3 "{&alpha} =.01") label(4 "{&alpha} =.001") size(4)) ///
>             title("Simulated Power Analysis; DD, 0-64, All Cause Mortality"
> " ", size(4))
.     graph export
"$dropbox/health_insurance_and_mortality/state_level_public
> _data_example/scripts/markdown/simulated_power_analysis.png",  replace
width
> (800)
(file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_publi
> c_data_example/scripts/markdown/simulated_power_analysis.png written in PNG
> format)
```

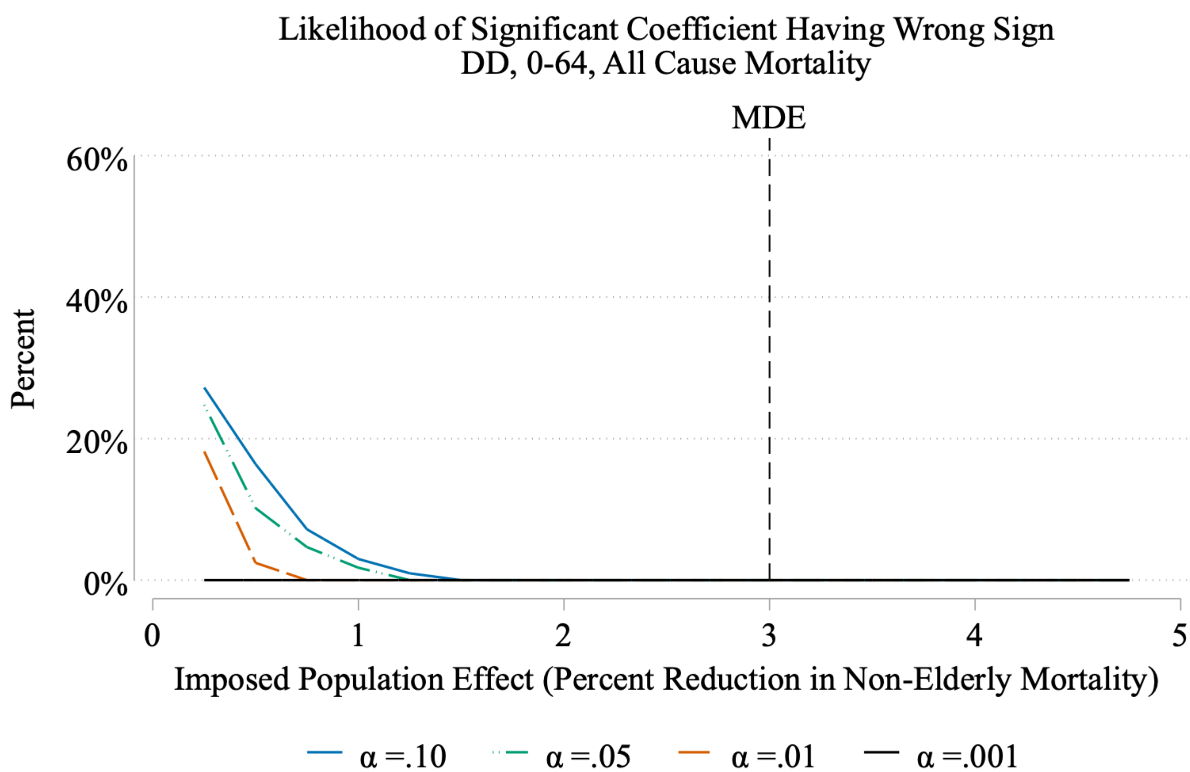


Simulated Power Analysis; DD, 0-64, All Cause Mortality

Plot sign error

```
. sum s_error_10

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
  s_error_10 |         19     2.88117    7.122931          0   27.21893

. gen  s_error_label= 62.5

. twoway connected s_error_10 effect_size ,  lpattern("l") color(sea)
msymbol(
> none) mlabcolor(sea) mlabel("") mlabsize(3) mlabpos(11) ///
>     || connected s_error_05 effect_size  ,  lpattern("..._")
color(turquoise)
>  msymbol(none) mlabcolor(turquoise) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected s_error_01 effect_size  , lpattern("_") color(vermillion)
m
> symbol(none) mlabcolor(vermillion) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected s_error_001  effect_size  ,  lpattern("l") color(black)
msy
> mbol(none) mlabcolor(black) mlabel("") mlabsize(3) mlabpos(3) ///
>     || scatter s_error_label effect_size  , mlabel(mde_label) msymbol(none)
>  mlabpos(12) mlabsize(4)  ///
>     ytitle("Percent", size(4)) ///
>         xtitle("Imposed Population Effect (Percent Reduction in Non-Elderly
> Mortality)", size(4)) ///
>         legend(size(4) order(1 2 3 4) pos(6) col(4) label(1 "{&alpha}
=.10")
```

```
>  label(2 "{&alpha} =.05") label(3 "{&alpha} =.01") label(4 "{&alpha}
=.001")
> ) ///
>          xscale(r(0 5)) ///
>          xline(`mde', lpattern(dash) lcolor(grey) noextend) ///
>          xlabel( , nogrid labsize(4)) ///
>          ylabel(0 "0%" 20 "20%"  40 "40%" 60 "60%",gmax noticks labsize(4))
/
> //
>          title("Likelihood of Significant Coefficient Having Wrong Sign"
"DD,
>  0-64, All Cause Mortality" " ", size(4))
(note:  named style grey not found in class color, default attributes used)
.     graph export
"$dropbox/health_insurance_and_mortality/state_level_public
> _data_example/scripts/markdown/s_error.png", replace width(800)
(file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_publi
> c_data_example/scripts/markdown/s_error.png written in PNG format)
```

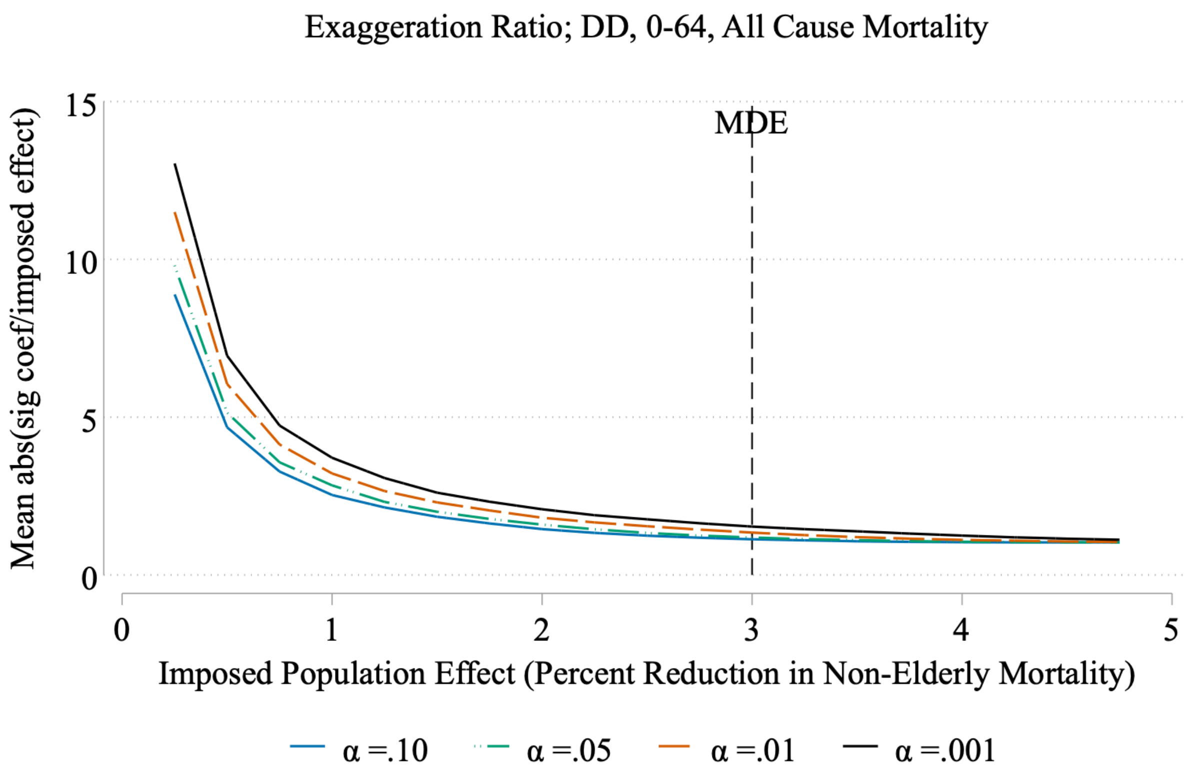


Likelihood of Significant Coefficient Having Wrong Sign DD, 0-64, All Cause Mortality

Plot magnitude error

```
. sum m_error_001

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
 m_error_001 |         19    2.851967    2.875496   1.114921   13.03762

. gen  height= `r(max)'*1.05
```

```
. twoway connected m_error_10 effect_size ,  lpattern("l") color(sea)
msymbol(
> none) mlabcolor(sea) mlabel("") mlabsize(3) mlabpos(11) ///
>     || connected m_error_05 effect_size ,  lpattern(".._") color(turquoise)
> msymbol(none) mlabcolor(turquoise) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected m_error_01 effect_size , lpattern("_") color(vermillion)
ms
> ymbol(none) mlabcolor(vermillion) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected m_error_001  effect_size ,  lpattern("l") color(black)
msym
> bol(none) mlabcolor(black) mlabel("") mlabsize(3) mlabpos(3) ///
>     || scatter height effect_size , mlabel(mde_label) msymbol(none)
mlabpos
> (12) mlabsize(4)  ///
>     ytitle("Mean abs(sig coef/imposed effect)", size(4)) ///
>         xtitle("Imposed Population Effect (Percent Reduction in Non-Elderly
> Mortality)", size(4)) ///
>         legend(size(4) order(1 2 3 4) pos(6) col(4) label(1 "{&alpha}
=.10")
>  label(2 "{&alpha} =.05") label(3 "{&alpha} =.01") label(4 "{&alpha}
=.001")
> ) ///
>         xscale(r(0 5)) ///
>         xline(`mde', lpattern(dash) lcolor(grey) noextend) ///
>         xlabel(, nogrid labsize(4)) ///
>         ylabel(, gmax noticks labsize(4)) ///
>         title("Exaggeration Ratio; DD, 0-64, All Cause Mortality"  " ",
size
> (4))
(note:  named style grey not found in class color, default attributes used)
.         graph export
"$dropbox/health_insurance_and_mortality/state_level_pu
> blic_data_example/scripts/markdown/m_error.png", replace width(800)
(file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_publi
> c_data_example/scripts/markdown/m_error.png written in PNG format)
```

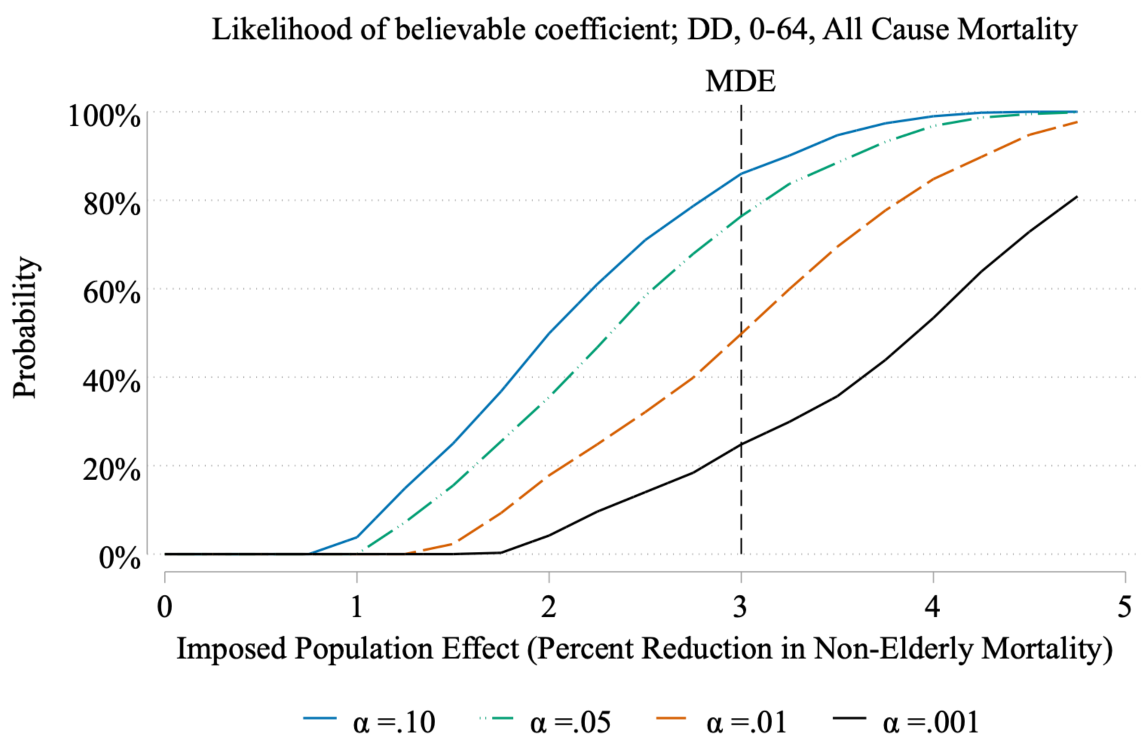


Exaggeration Ratio; DD, 0-64, All Cause Mortality

Plot believability

```
. twoway connected believe_10 effect_size ,  lpattern("l") color(sea)
msymbol(
> none) mlabcolor(sea) mlabel("") mlabsize(3) mlabpos(11) ///
>     || connected believe_05 effect_size ,  lpattern(".._") color(turquoise)
> msymbol(none) mlabcolor(turquoise) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected believe_01 effect_size , lpattern("_") color(vermillion)
ms
> ymbol(none) mlabcolor(vermillion) mlabel("") mlabsize(3) mlabpos(3) ///
>     || connected believe_001  effect_size ,  lpattern("l") color(black)
msym
> bol(none) mlabcolor(black) mlabel("") mlabsize(3) mlabpos(3) ///
>     || scatter full_power effect_size , mlabel(mde_label) msymbol(none)
mlab
> pos(12) mlabsize(4)  ///
>     xtitle("Imposed Population Effect (Percent Reduction in Non-Elderly
Mort
> ality)", size(4)) ///
>         legend(size(4) order(1 2 3 4) pos(6) col(4) label(1 "{&alpha}
=.10")
>  label(2 "{&alpha} =.05") label(3 "{&alpha} =.01") label(4 "{&alpha}
=.001")
> ) ///
>                 ytitle("Probability", size(4)) ///
>         xscale(r(0 5)) ///
>         xline(`mde', lpattern(dash) lcolor(grey) noextend) ///
>         xlabel(, nogrid labsize(4)) ///
```

```
>         ylabel(0 "0%" 20 "20%"  40 "40%" 60 "60%" 80 "80%" 100 "100%",gmax
n
> oticks labsize(4)) ///
>         title("Likelihood of believable coefficient; DD, 0-64, All Cause
Mor
> tality" " ", size(4))
(note:  named style grey not found in class color, default attributes used)
.      graph export
"$dropbox/health_insurance_and_mortality/state_level_publi
> c_data_example/scripts/markdown/believable.png", replace width(800)
(file
/Users/hollinal/Dropbox/health_insurance_and_mortality/state_level_publi
> c_data_example/scripts/markdown/believable.png written in PNG format)
```



Likelihood of believable coefficient; DD, 0-64, All Cause Mortality

Conclusion

Using this simple example, we can see that for this simple research design the minimum mortality reduction that is believable, well-powered, and significant at the 5% level is around 3%. Changing the research design (e.g. adding control variables, shifting to the county-level, changing the cause of death) would certainly impact power.

This simple research design is a DiD comparing 23 random treated states to 18 random control states. In this simple design we used 5 years of pre-expansion data and 3 years of post-expansion data. Both state and year fixed-effects were included. Regressions were weighted by state-population and standard errors were clustered at the state-level. The dependent variable was the natural log of the all-cause non-elderly mortality rate per 100,000.