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Abstract

This paper examines the impact of Medicaid expansions to parents and childless adults on adult mortality. Specifically, we evaluate the long-run effects of eight state Medicaid expansions from 1994 through 2005 on all-cause, healthcare-amenable, non-healthcare-amenable, and HIV-related mortality rates using state-level data. We utilize the synthetic control method to estimate effects for each treated state separately and the generalized synthetic control method to estimate average effects across all treated states. Using a 5% significance level, we find no evidence that Medicaid expansions affect any of the outcomes in any of the treated states or all of them combined. Moreover, there is no clear pattern in the signs of the estimated treatment effects. These findings imply that evidence that pre-ACA Medicaid expansions to adults saved lives is not as clear as previously suggested.

Keywords: Medicaid, healthcare-amenable mortality, all-cause mortality, generalized synthetic control method, public health, healthcare reform

JEL Classifications: I13, I18, I38

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1. Introduction

Theoretically, Medicaid may reduce mortality risk by improving access to medical care, which in turn may lead to improved physical and mental health. However, whether Medicaid in fact reduces adult mortality is the subject of debate in the literature. We contribute new evidence to this debate by using synthetic control and generalized synthetic control approaches to investigate the long-run mortality effects of several state Medicaid expansions in the 1990s and 2000s.

Several studies aim to estimate the causal effect of Medicaid on mortality. In a highly influential study evaluating Medicaid expansions in three states in the early 2000s, Sommers et al. (2012) find a statistically significant reduction in adjusted all-cause mortality of 6.1 percent compared to adjacent control states. However, the effect is completely driven by one of the three treatment states, New York, so the extent to which the results are generalizable to the entire U.S. is unclear. Additionally, by using county-level mortality data to study state-level expansions, the study overstates the amount of independent variation, thereby potentially leading to greater precision than is warranted and spurious findings of statistical significance. Traditional solutions in these situations, like clustering the standard errors by state, would not resolve the problem since there are few states (three treated and four control) in the sample (Bertrand, Duflo, and Mullainathan, 2004). Furthermore, Kaestner (2012) questions the validity of Sommers et al.'s (2012) difference-in-differences (DID) design because pre-intervention mortality trends in the treatment and control states exhibit statistically significant differences.

Sommers (2017) aims to rebut the latter of these critiques by using propensity-score matching to construct the control group, finding that all-cause and healthcare amenable mortality declined by 6 and 6.7 percent, respectively, across the same three Medicaid expansion states and

again using county-level data. He also finds a substantial reduction in HIV-related mortality.

In another prominent study, Finkelstein et al. (2013) find no evidence of an effect of a randomized Medicaid expansion in Oregon on adult mortality. However, the analysis may have lacked sufficient statistical power to detect reasonably sized effects given the relatively small number of deaths in the sample.

A few newer studies examine the effects of the more recent Medicaid expansions under the Affordable Care Act on mortality. Black et al. (2022) argue that the ACA lacks sufficient power for the detection of plausible mortality effects due to the modest marginal take-up of health insurance in Medicaid expansion versus non-expansion states relative to the overall population. However, two other concurrent studies do find evidence of effects. Borgschulte and Vogler (2020) find a 3.6 percent decrease in all-cause mortality for adults between the ages 20 to 64 following the ACA Medicaid expansion using data from the restricted access file of the National Vital Statistics System of the CDC. Miller et al. (2021) find a 9.4 percent reduction on mortality rates of adults aged 55 to 64 years after linking information from the American Community Survey to administrative data from the Census Numident file. Both ACA analyses are inherently short-run due to the recent nature of the policy, and effects could become either stronger or weaker in the long run. Moreover, the ACA's expansions, which were accompanied by great publicity, substantial outreach expenditures, and an overhaul of the health care system along several dimensions, may not affect health the same way as other state expansions.

The purpose of this paper is to examine the effect of the largest state Medicaid expansions in the 1990s and 2000s on all-cause, healthcare-amenable, non-healthcare-amenable, and HIV-related adult mortality using state level mortality data. By doing so, we revisit the analyses of Sommers et al. (2012) and Sommers (2017), but with several important differences.

First, we use more expansion states – eight instead of three – because we include not only expansions of traditional Medicaid but also those made through a Section 1115 waiver.[1] Second, we examine a longer time horizon – nine post expansion years instead of the six used by Sommers (2017) and the even smaller period used by Sommers et al. (2012).[2] This is an important distinction as one may expect effects on mortality to be gradual since health capital accumulates as a stock (Grossman, 1972). However, it is also possible that mortality reductions emerge in the short run and then disappear if there is pent-up demand when individuals first become insured. Third, we use state-level mortality data instead of county-level data. Since Medicaid expansions happened at the state level, and not at the county level, using state-level data guards against potentially overstating statistical significance, as noted above. Fourth, we estimate state-specific causal effects using the synthetic control method (SCM) developed by Abadie, Diamond, and Hainmueller (2010). To estimate the overall causal effect of state Medicaid expansions on mortality across all treated states, we use a generalized synthetic control method (GSCM), an extension of the SCM that allows for multiple treatment groups and different treatment timing (Xu, 2017). These methods allow the data to determine the appropriate control group rather than relying on hand-matching of border states, as in Sommers et al. (2012). Additionally, while the propensity score matching method of Sommers (2017) is also data-driven, it only allows for matching on observable covariates, whereas SCM and GSCM also allow for matching on pre-treatment levels and trends in the outcome variable.

Using a 5% significance level, our SCM and GSCM results provide no evidence of any

[1] The expansion states included in our analysis are AZ, IL, ME, MI, NM, NY, OR, and VT. The expansion states included in both Sommers papers are AZ, ME, and NY.

[2] Sommers, 2012 uses 5 post expansion years. We use nine post expansion years, inclusive of the year of the Medicaid expansion, to estimate the overall causal effect of state Medicaid expansions across all treated states using GSCM and the state level causal effects using SCM.

effects of expanding Medicaid on all-cause, healthcare-amenable, non-healthcare-amenable, or HIV-related mortality, either in any of the treated states separately or in all of the treated states combined. The only estimate that is even significant at the 10% level is a reduction in *non*-healthcare-amenable mortality in Illinois. Moreover, there is no clear pattern in the signs of the coefficient estimates, as there are roughly equal numbers of positives and negatives.

The main implication of our results, when combined with the prior literature, is that one should not assume that state Medicaid expansions automatically lead to reductions in adult mortality. Instead, the effects of each expansion are likely dependent on a number of factors, such as the availability of services and providers for Medicaid enrollees, the demographic characteristics of the population, and other concurrent changes in the health care system.

2. Data

Prior to the enactment of the ACA Medicaid expansions in 2014, 16 states expanded Medicaid coverage (Centers for Medicare & Medicaid Services, 2022; Kronick and Gilmer, 2002; Mann, 2002; Coughlin and Zuckerman, 2008; Atherly et al., 2012). These Medicaid expansions differed in terms of their scope of coverage, pre-existing eligibility levels, targeted adult groups, and benefit design as described in Table 1. For instance, income eligibility thresholds ranged from 35% of the FPL to 200% of the FPL. To address the non-uniform nature of these expansions and establish a strong implied first-stage of Medicaid insurance take-up, we focus on states with *sizable* expansions of coverage, measured by the number of Medicaid beneficiaries per capita.

To determine what constitutes "sizable" expansions, we use two-sample t-tests to assess the magnitude and statistical significance of the increase in the number of Medicaid beneficiaries

per capita in the five years following the expansion or [t+1, t+5] (excluding the expansion year) relative to the five years prior or [t-5, t-1]. We then define a "sizeable" expansion as one of at least 3.5 percentage points, where that number is chosen because it approximately corresponds to the smallest increase in the three states classified as treated by Sommers et al. (2012) and Sommers (2017) (3.8 percentage points in New York). Applying this rule, we are left with 10 states with sizable expansions of coverage. From those, we drop Massachusetts because the expansion occurred as part of a broader health care reform that also included a large expansion of subsidized private coverage. We also drop Tennessee because its expansion was followed by a contraction within our post-treatment period, diluting the potential long-run impact. Ultimately, then, we classify eight states as treated: Arizona, Illinois, Maine, Michigan, New Mexico, New York, Oregon, and Vermont.

We use the Compressed Mortality File of the Centers for Disease Control and Prevention (CDC) from 1980 to 2013. Our main outcome of interest is all-cause mortality per 100,000 adults ages 20-64. In addition, we examine mortality amenable by healthcare, mortality non-amenable by healthcare, and HIV-related mortality per 100,000 adults ages 20-64.[3] We would not generally expect Medicaid to have much influence on mortality from conditions that cannot be influenced by health care. Therefore, the analyses for non-healthcare-amenable mortality can be loosely interpreted as placebo tests. HIV-related mortality can be considered a relatively extreme example of healthcare-amenable, as it is always fatal when untreated and almost never fatal when treated with expensive medications.

[3] Following Nolte and McKee (2012), healthcare amenable mortality is defined as deaths potentially preventable given effective and timely health care from the following causes of death as classified by the International Classification of Diseases (10th revision): infectious diseases (A00-9, A15-9, A35, A36, A37, A80, B05, B90), tumors (C18-21, C44, C50, C53, C54, C55, C62, C81, C91-5), diabetes (E10-4), heart (I20-5, I05-9, I10-3, I15, I60-9) and respiratory (J00-9, J20-99, J10-1, J12-8) diseases as well as surgical (K25-7, K35-8, K40-6, K80-1, N00-7,N17-9, N25-7, N40), maternal (O00-99, Q20-8), pre-natal (P00-96, A33) or other (E00-7, G40-1) conditions.

Our regressions include control variables for annual state-level unemployment rate, median income, number of Medicaid beneficiaries and the following percentages: poverty rate; married; female; high school degree (among those 25 and older); population aged 20-34, 35-44, 45-54, and 55-64; and race/ethnicity white, Hispanic or other. Socio-economic characteristics were obtained from the Bureau of Labor Statistics, demographic information comes from the Census, and Medicaid enrollment data are sourced from the University of Kentucky Center for Poverty Research.[4] Summary statistics are given in Appendix Table A.1.

3. Econometric Methods

3.1 Difference-in-Differences

We begin with a naïve difference-in-differences design (DID) to examine mortality in 8 expansion states using 35 non-expansion states as controls. States that had a Medicaid expansion that we do not include in the treatment group, for the reasons discussed above, are omitted from the sample. The DID estimate shows the effect of Medicaid on mortality rate in all expansion states over the span of two decades relative to the national average in non-expansion states. Implicitly, this approach uses a linear combination of the untreated units with coefficients that sum to one. In other words, the regression estimator could also be considered as a weighting estimator with weights that sum up to one. However, there is no restriction on the values these weights may take, enabling extrapolation outside the support of the data (Abadie, Diamond, and Hainmueller, 2014).

[4] University of Kentucky Center for Poverty Research. (2020, May). UKCPR National Welfare Data, 1980-2018. Lexington, KY.

The identifying assumption for a causal interpretation of the parameter of interest in the DID design is that, conditional on the other covariates, pre-intervention changes in mortality would have been the same in expansion and non-expansion states in the absence of the intervention ("parallel trends"). Given numerous possible reasons to doubt the validity of this assumption, we do not consider the DID estimates to reflect causal effects. Instead, we show them purely for the purpose of comparison to our preferred approaches. We present DID estimates both for the whole sample and for samples including just one treated state at a time.

In the absence of individual-level information where Medicaid eligibility or enrollment could be matched to mortality, it is important to stress that the effects should be interpreted as intent-to-treat effects of legislative expansion of Medicaid eligibility levels on mortality rates. The direct effect of Medicaid on the newly enrolled beneficiaries cannot be ascertained with the aggregate date we use and, thus, our coefficient estimates do not reflect the treatment effect on the treated population or on average.

We estimate the following specification in the DID design:

$$Mortality\ Rate_{it} = \beta_0 + \rho MedicaidExpansion_{it} + \boldsymbol{X}'\boldsymbol{\beta} + \mu_t + \Omega_i + \varepsilon_i \qquad (1)$$

where i and t index state and year, respectively. $MedicaidExpansion_{lt}$ indicates whether state i expanded Medicaid in year t. $\boldsymbol{X}$ is a vector of demographics (percentage of the population that is white, black, Hispanic, female, and age indicators for groups 20-34, 35-44, 45-54, and 55-64 years old), poverty rate, logarithm of median income (measured in constant 2012 dollars), unemployment rate, and percentage of the population with a high school diploma and percentage of the population that is married. Finally, we include year and state fixed effects μ_t and Ω_i, respectively. We present unweighted estimates so that they can be interpreted as the effect of the average Medicaid expansion (as opposed to the effect on the average person in the U.S.

population). The parameter of interest is β_1, which denotes the effect of the state Medicaid expansion on each mortality rate of interest.

3.2 Synthetic Control

Next, we turn to the SCM, a data-driven procedure introduced by Abadie et al. (2010), with the intention to examine the effect of state Medicaid expansions on adult mortality on each individual state. For each treated state, the control state is a weighted average of states that did not expand Medicaid and that most closely resemble pre-intervention mortality. The intuition behind the approach is that a combination of units often provides a better comparison for the unit exposed to the intervention than any single unit alone. This offers reasonable counterfactuals of mortality rates in treated states if the expansion had not occurred. The procedure reweights the control group such that the synthetic control expanding states match observable characteristics and pre-intervention mortality values. Unlike the regression approach, the SCM estimator assigns weights ranging between zero and one to shield off extrapolation bias. This prevents estimation of "extreme counterfactuals" by forcing to show the proximity between treated and control.

For identification, a SCM makes two implicit assumptions. First, there exists no interference between units that comprise the donor pool (Rosenbaum, 2007). Given the state-specific nature of the expansion and our state-year panel, this holds by design. More importantly, unbiasedness requires that there exists a synthetic control with a vector of weights

$$\boldsymbol{W}^* = \left\{w_2^*, \dots, w_{J+1}^* \middle| w_j^* \geq 0 \; for \; j = 2, \dots, J+1 \; , w_2^* + \cdots w_{J+1}^* = 1\right\} \tag{2}$$

a vector $\boldsymbol{Z}_i$ of observed covariates (unaffected by the intervention), and a vector $\boldsymbol{\mu}_i$ of unknown factor loadings such that

$$\sum_{j=2}^{J+1} w_j^* \boldsymbol{Z}_j = \boldsymbol{Z}_1, \sum_{j=2}^{J+1} w_j^* \boldsymbol{\mu}_j = \boldsymbol{\mu}_1 \quad (3)$$

Even if equation (2) holds only approximately for a synthetic control that fits well but not perfectly the treated state, the bias of the estimator will tend to zero as the number of pre-intervention treatment periods increases. For the DID and SCM analyses, the post-intervention period starts the first full year after the Medicaid expansions and it extends for 8 years. The estimated treatment effect uses information from both the intervention and the 8 post-intervention years and represents the average change in mortality rates in each state over a total of 9 Medicaid expansion years. The pre-intervention period is defined as the 13 years leading up to the expansion. This is the maximum common number of pre- and post-intervention years that can be accommodated for all states. By using the same number of pre- and post-treatment periods for each state, we can easily transition into the national-level estimation where we pool all treated and all control units together.

Inference is based on placebo tests in time and space. The placebo test in space estimates the probability of finding mortality reductions of the magnitude of the observed reduction in treated states under a random permutation of the expansion to generate the p-values of our estimated effects. To implement the SCM numerically, we solve a nested optimization problem. First, we minimize the multivariate distance between values of mortality predictors $MortalityRateLags_{it}$ and $\boldsymbol{X}$ of states expanding Medicaid to their corresponding synthetic controls subject to weight constraints $\boldsymbol{W}$ ranging [0,1]. Then, we introduce matrix $\boldsymbol{V}$ that applies different weights to each mortality predictor depending on each predictive power. Our choice of $\boldsymbol{V}$ assigns weights that minimize the mean square error of the synthetic control estimator.

Based on weights calculated by the SCM, our main results come from estimation of the factor model in equation (3) below:

$$Mortality\ Rate_{it} = \delta_t + \boldsymbol{Lags}'\boldsymbol{\mu} + \boldsymbol{X}'\boldsymbol{\beta} + \boldsymbol{\lambda_t}\boldsymbol{\mu_i} + \varepsilon_{it} \quad (4)$$

where i indexes state and t year. The parameter δ_t is an unobserved, common, time-dependent factor. $\boldsymbol{X}$now contains a larger set of observed state-year demographic and socio-economic information; namely, the percentage of the population that is white, black, Hispanic, female, and age indicators for groups 20-34, 35-44, 45-54, and 55-64 years old, poverty rate, logarithm of median income, unemployment rate, and percentage of the population with a high school diploma and percentage of the population that is married as previously and, additionally, logarithm of population and logarithm of Medicaid beneficiaries.. The term $\boldsymbol{\lambda_t}\boldsymbol{\mu_i}$ captures heterogeneous responses to multiple observed factors. Finally, $\boldsymbol{Lags}$is a vector of year indicators including lagged outcome terms. The choice of the latter is data-driven and based on which lag results to the lowest Mean Squared Prediction Error (MSPE). However, we refrain from using more than two pre-treatment outcome lags in any specification to avoid overfitting and use the average pre-expansion mortality rate, and in most specifications, a one-year lag and a ten-year lag.

3.3 Generalized Synthetic Control

Finally, we use a GSCM approach to estimate the overall average effect that the various state-level Medicaid expansions had on adult mortality. GSCM combines the SCM with linear interactive fixed effects models introduced by Xu (2017). GSCM generates counterfactuals for each Medicaid-expanding state using information from non-expanding states by estimating a linear interactive fixed effects model of state-specific intercepts interacted with time-varying

coefficients. Unlike the SCM, the GSCM estimator performs "dimension reduction prior to reweighting" to ensure the values of the control variables are smooth across non-Medicaid expanding states. This is akin to bias-correction in the presence of heterogeneous treatment effects across states which is the case in this analysis. The GSCM has several appealing features which are relevant to our analysis. Contrary to the state specific SCM, it is much more flexible since it allows for multiple treated states that may have expanded at different years. This permits the estimation of a single, policy-informative intent-to-treat effect for all Medicaid-expanding states to the estimation of eight, state-specific estimates for each state that expanded Medicaid in the sample. In addition, it generates conventional p-values based on frequentist statistics for uncertainty analysis as opposed to pseudo p-values from randomization inference leading to increased efficiency given correct model specification. Finally, it uses a cross-validation techniques for the selection of control variables that minimizes concerns of overfitting. For more details on the GSCM, please refer to Xu (2017). O'Neill et al. (2020) provide a comparison of DID, SCM, interactive fixed effects (IFE) and GSCM methods in the context of evaluating hospital practices in England. GSCM emerges as the preferred method in their analysis on the basis of simulation results indicating it outperforms the other methods in robustness to the assumption of parallel trends and heterogeneous effects, echoing results in Xu (2017).

For identification and estimation, the GSCM makes five implicit assumptions. First, the error term of any state at any year is not correlated with the decision to expand Medicaid, observed controls, as well as "unobserved cross-sectional and temporal heterogeneities" of all states, including the state itself, at all years (strict exogeneity). Second, the treatment indicator can be correlated with both observed control and the interaction of unobserved factors with their factor loadings for any state at any year. Third, for consistent estimation, there may be weak

serial dependence of the error terms, but they are required to be independent of controls while error terms of different states are uncorrelated. Fourth, convergence of the GSCM estimator relies on specific moment conditions. Finally, for valid inference it is also assumed that error terms are cross-sectionally independent and homoscedastic, albeit they can be heteroscedastic across time.

It should be noted that inference is carried out for the intent-to-treat effect based on the drawn sample, not the entire population, implying no uncertainty estimates for the individual, state-specific intent-to-treat effects, just for final intent-to-treat effect of all Medicaid expansions on mortality. Moreover, these estimates are based on a post-intervention period which includes the Medicaid expansion year, and, thus, spans 9 years and a pre-intervention period of 13 years.

Our main results come from estimation of the linear factor model in equation (5) below:

$$Mortality\ Rate_{it} = \delta_{it} D_{it} + \boldsymbol{X}'\boldsymbol{\beta} + \boldsymbol{\lambda_i f_t} + \varepsilon_{it} \quad (5)$$

where i indexes state and t year. The variable D_{it} denotes whether state *i* in year *t* has expanded Medicaid ($D_{it} = 1$) or not ($D_{it} = 0$) and parameter δ_{it} is the heterogeneous intent-to-treat effect on state *i* at year *t*. The vector $\boldsymbol{X}$ contains observed state-year demographic and socio-economic information; namely, the percentage of the population that is white, black, Hispanic, female, and age indicators for groups 20-34, 35-44, 45-54, and 55-64 years old, poverty rate, logarithm of median income, unemployment rate, and percentage of the population with a high school diploma and percentage of the population that is married. The vector $\boldsymbol{f_t}$ is a collection of unobserved common factors whereas parameter vector $\boldsymbol{\lambda_i}$ has the associated factor loadings. A cross-validation procedure is followed to select the number of unobserved factors that identifies that three factors minimize MSPE. Taken together, the term $\boldsymbol{\lambda_i f_t}$ captures heterogeneous responses to multiple unobserved factors.

We calculate the average intent-to-treat effect (ITT) for all states *i* at year *t* as follows:

$$ITT_t = \frac{1}{N_{tr}} \sum_i [Mortality\ Rate_{treated,t} - Mortality\ Rate_{control,t}] = \frac{1}{N_{tr}} \sum_i \delta_{it} \quad (6)$$

where N_{tr} denotes the number of states that expanded Medicaid in year *t* while $Mortality\ Rate_{treated,t}$ and $Mortality\ Rate_{control,t}$ the mortality rate in states that did and did not expand Medicaid, respectively. The uncertainty estimates of the GSCM estimator are computed via parametric bootstrap using 1000 runs.

4. Results

4.1 National Analyses

We begin our discussion of results with the naïve DID estimates from analyses that pool together all treated and control states. In the row labeled "Difference-in-differences" in Table 2 we see that, using the joint sample of US states, the DID estimates are negative for all four mortality outcomes, indicating that expanding Medicaid saves lives. Our estimate for all-cause mortality is 11.7 fewer deaths per 100,000 adults, which is smaller than Sommers et al.'s (2012) estimate of 19.6. Also, due likely to our use of state-level rather than county-level data, our standard errors are more conservative, and none of the estimates are statistically significant. Moreover, Sommers et al.'s (2012) point estimate for all-cause mortality would not be significant either with our standard error. Our point estimates represent 3.3%, 5.2%, 3.0%, and 17.3% of the baseline means of all-cause, healthcare-amenable, non-healthcare-amenable, and HIV-related mortality, respectively. Based on the low end of the 95% confidence intervals, we can rule out reductions in mortality larger than 12.0%, 14.9%, 11.8%, and 94.0%. The effect on

HIV-related mortality, in particular, is therefore potentially quite large, even though we cannot conclude that it is statistically different from zero.

Next, we turn to the GSCM results, shown in the row labeled "Generalized synthetic control method" in Table 2. Using this more rigorous method flips three of the four coefficient estimate signs to positive, and all four estimates are statistically insignificant. For the only outcome for which Medicaid expansion continues to be associated with reduced mortality, healthcare-amenable mortality, the magnitude represents .53% of the baseline mean. Based on the confidence intervals, we can rule out reductions in all-cause, healthcare-amenable, non-healthcare-amenable, and HIV-related mortality of greater than 4.3%, 9%, 3.9%, and 42.9%, respectively. Figure 1 plots mortality rate trends in treated states and the synthetic counterfactual based on GSCM. Figure 2 reports the GSCM estimate of Medicaid's ITT effect graphically, with separate coefficients for each year relative to Medicaid expansion.[5] The figure shows that for all four outcomes the pre-treatment trends are quite flat and close to zero, and a Wald test ,for a related IFE specification not reported here, reveals no differential pre-treatment trends between the expansion and non-expansion states. This provides evidence to support the parallel trends assumption, therefore supporting a causal interpretation of the post-treatment results.

In sum, when using our preferred method, the GCSM, to evaluate the average effect of expanding Medicaid among expanding states, we find signs and point estimates that are consistent with either no effect or a relatively small effect on all-cause and different types of mortality. However, the relatively imprecise nature of the estimates means that we cannot

[5] Please, note GSCM's graphical convention under which the vertical line in the GSCM figures marks the end of the pre-intervention period and is, thus, included in the 13 pre-expansion years of the study sample as opposed to the 9 expansion years that follow.

conclusively rule out sizeable effects, particularly for healthcare-amenable and HIV-related mortality.

4.2 Separate Analyses for Each State

Next, we narrow-in on each state that expanded Medicaid. The row labeled "Difference-in-differences" in panels A and B of Table 3 reports the state-specific DID estimates of the intent-to-treat effect of state Medicaid expansions on the all-cause mortality rate per 100,000 adults aged 20-64, along with their standard errors in parentheses. We observe statistically significant and relatively large estimates for all-cause mortality in three states. In two of these states – Illinois and New York – Medicaid expansions are associated with lower mortality, while in the third – New Mexico – the association is actually positive (more mortality). Since there is little theoretical reason for Medicaid expansions to *increase* mortality, the existence of such a positive "effect" calls into question the validity of the DID research design. In the other five states, Medicaid expansion is statistically insignificant and its point estimate is relatively small; its sign is negative in Arizona and Vermont and positive for Maine, Michigan, and Oregon. Broadly, these single-state DID results are in line with those from Sommers et al. (2012): they and we both find a statistically significant all-cause mortality reduction in New York, a null effect in Arizona, and a sign flip to positive for Maine.

These state-by-state results show why we find a somewhat smaller overall effect of all Medicaid expansions than did Sommers et al. (2012). In the five states we examined that they did not, there is no discernable pattern of results (one negative and significant estimate, one positive and significant estimate of roughly the same size, one negative and insignificant estimate, and two positive and insignificant estimates). Therefore, one would expect the overall effect size to be attenuated relative to a sample with only three treated states that includes the one with the

largest mortality reduction. Recall that one of the questions we set out to answer was whether New York's experience of a large mortality reduction from expanding Medicaid was an exception or the rule. These results suggest that it was an exception.

Next, we turn to the SCM results for all-cause mortality, reported in the row labeled "Synthetic control method" in Panels A and B of Table 3. P-values from permutation tests are in brackets below the point estimates. We observe no statistically significant estimates for any of the eight states, and there is no clear pattern of signs (five negative, three positive). Moreover, using the SCM method substantially attenuates the large point estimates observed with DID for Illinois, New Mexico, and New York. New York's, for instance, shrinks by 76%, and its p-value rises to a very high 0.75. In other words, once more rigorous methods are used, even New York's experience with expanding Medicaid may not be as beneficial as first thought.

Turning to healthcare-amenable mortality rates in Table 4, we observe broadly similar results. Using DID, we find significant reductions in healthcare-amenable mortality rates in Illinois, New York and Vermont but increases in New Mexico. The point estimates in the other four states are small and statistically insignificant, with two being positive and two negative. When using SCM, all significance disappears, and the effect sizes in Illinois, New York, Vermont, and New Mexico shrink dramatically.

Results for non-healthcare-amenable mortality are shown in Table 5. We observe statistically significant results in four of the eight states when using DID: mortality reductions in Illinois and New York and increases in Maine and New Mexico. Moreover, the effect sizes for non-healthcare-amenable mortality in those states are all *larger* than those for healthcare-amenable mortality. This seems theoretically implausible and therefore questions the validity of the DID research design. Two of the four insignificant estimates are positive and the other two

are negative. When using SCM, the results all become insignificant, with the exception of a marginally significant and relatively small reduction in Illinois. Moreover, the largest point estimates (those in Illinois, New Mexico, and New York) all shrink dramatically. Four estimates are positive and the other four negative.

Finally, Table 6 reports results for HIV-related mortality rates. Data are not available for Maine and Vermont, so we examine only the six remaining states. Using DID, we observe a large, significant reduction in mortality in New York, as well as smaller but significant (at the 10% level or better) increases in mortality in Michigan and New Mexico. In the other states, two coefficient estimates are positive and the other negative. Using SCM, there are again no statistically significant effects, and the largest ones found when using DID are substantially attenuated. Five estimates are negative and only one positive; given the lack of statistical significance, this could merely be a coincidence.

The figures in the online appendix depict the single-state synthetic control results graphically. We plot the all-cause mortality rate trend in each of the eight treated states and their synthetic counterfactuals. We also report the SCM estimate of Medicaid's ITT effect on all-cause mortality graphically, with separate coefficients for each year of treatment time.

Overall, then, our results indicate mixed patterns of signs and significance when using DID, and a mixed pattern of signs with no statistical significance (at the 5% level) when using SCM. We therefore are unable to conclude that the Medicaid expansions had any discernable effects on any of the mortality outcomes in any of the expansion states.

5. Conclusion

This paper evaluates the effect of eight state Medicaid expansions in the 1990s and 2000s on state-level mortality rates, including all-cause, healthcare amenable, non-healthcare-

amenable, and HIV-related mortality. Our preferred methods are GSCM for a pooled nationwide analysis and SCM for one-state-at-a-time analyses. Using these methods, we find no evidence that Medicaid expansion reduces any of the four mortality measures in any individual state or across all treated states as a whole. Estimates are never statistically significant at the 5% level, the pattern of signs is mixed, and magnitudes are generally small. However, the confidence intervals in some cases are quite wide – most notably for the whole-country analyses of healthcare-amenable and HIV-related mortality. This is consistent with Black et al.'s (2022) argument that the aggregate-level information we rely on might have limited ability to detect mortality reductions. We therefore stop short of claiming that our results show conclusively that Medicaid expansions do not have any effect on mortality at all. Rather, we argue merely that the evidence that pre-ACA Medicaid expansions to adults saved lives is not as clear as suggested by previous research (Sommers et al., 2012; Sommers 2017).

Our findings stand in contrast to results from recent studies on the ACA Medicaid expansion. Miller et al. (2019) found a statistically significant reduction in mortality of 9.4 percent – a magnitude that we can rule out according to our 95% confidence interval for the GSCM estimate for all-cause mortality. A plausible explanation for this discrepancy is the fact that Miller et al. (2019) focused exclusively on a relatively less healthy age group, the near elderly aged 55-64 years. In unreported regressions (available upon request), we repeat our analyses restricting the sample to 45-64 year olds, which is more similar to Miller et al.'s (2019) age profile. Using the GSCM, we estimate null ITT effects of Medicaid expansions on nationwide all-cause (δ = 4.719 all-cause deaths per 100,000 individuals, SE=17.364), healthcare-amenable (δ = -3.879 healthcare-amenable deaths per 100,000 individuals, SE=7.295), healthcare non-amenable (δ = 6.253 healthcare non-amenable deaths per 100,000 individuals,

SE=13.324), HIV-related (δ = 1.429 HIV-related deaths per 100,000 individuals, SE= 4.024) mortality rates of adults between 45 and 64 years old. Since the effect on healthcare amenable mortality, the outcome most likely influenced by Medicaid expansions, becomes an order of magnitude more negative, the evidence is somewhat stronger for reduced mortality for this age-restricted sample than for the full sample of non-elderly adults; however, Miller et al.'s (2019) results are much less ambiguous. Additionally, Borgschulte and Vogler (2020) use county-level information and find a 3.6 percent mortality reduction in matched counties following ACA Medicaid expansions. This magnitude is within the 95% confidence interval from our GCSM regression for all-cause mortality, so even though our conclusion differs from theirs, the results are not necessarily conclusively different.

All that said, it is plausible that the ACA Medicaid expansions could have reduced mortality even if prior state Medicaid expansions did not. The ACA expansions were widely publicized and occurred amidst much fanfare, potentially leading to greater take-up (and therefore clearer mortality effects) than prior state expansions. Consistent with this theory, Frean et al. (2017) found evidence of a "woodwork effect" from the ACA's Medicaid expansion, where individuals who were eligible for Medicaid even before the ACA took up coverage as a result of the ACA. In that case, it is not obvious that evidence from the ACA expansions is more relevant for future state-level expansions than our evidence from pre-ACA state expansions. Future one-state-at-a-time expansions presumably would not occur alongside widespread fanfare about sweeping health care reform. Circumstances surrounding their adoption may well be more similar to those from the 1990s and 2000s expansions that we study.

In short, the effect of Medicaid expansions on mortality could vary across time, space, age, take-up rate, and a host of other factors. Nonetheless, our consistent finding of null effects

with mixed signs and modest magnitudes across eight expansions in eight different states over two decades is noteworthy.

References

Abadie, A., Diamond, A., & Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of American Statistical Association*, 493-505.

Atherly, A., Dowd, B. E., Coulam, R. F., & Guy, G. (2012). The Effect of HIFA Waiver Expansions on Uninsurance Rates in Adult Populations. *Health Services Research*, 47(3pt1), 939-962.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How Much Should we Trust Differences-in-Differences Estimates. *Quarterly Journal of Economics*, 249-275.

Black, B., Hollingsworth, A., Nunes, L., & Simon, K. (2022). Simulated power analyses for observational studies: An application to the affordable care act medicaid expansion. Journal of Public Economics, 213, 104713.

Borgschulte, M., & Vogler, J. (2020). Did the ACA Medicaid Expansion Save Lives?. *Journal of Health Economics*, 102333.

Centers for Medicare & Medicaid Services. (2022). "State Waivers List." https://www.medicaid.gov/medicaid/section-1115-demo/demonstration-and-waiver-list/index.html. Accessed August 29, 2022.

Coughlin, T. A., & Zuckerman, S. (2008). State responses to new flexibility in Medicaid. The Milbank Quarterly, 86(2), 209-240.

Finkelstein, A. N., Taubman, S., Wright, B. J., Bernstein, M., Gruber, J., Newhouse, J., & Baicker, K. (2013). The Oregon Health Insurance Experiment; Evidence from the First-Year. Boston, MA: NBER Working Papers 17190.

Frean M, Gruber J, Sommers BD. Premium subsidies, the mandate, and Medicaid expansion: coverage effects of the Affordable Care Act. *Journal of Health Economics*, 2017;53:72-86.

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *Journal of Political economy*, *80*(2), 223-255.

Kaestner, B. (2012). Mortality and Access to Care after Medicaid Expansions. *New England Journal of Medicine*, 2453-4.

Kronick, R., & Gilmer, T. (2002). Insuring low-income adults: does public coverage crowd out private?. Health affairs, 21(1), 225-239.

Lykens, K. A., & Jargowsky, P. A. (2002). Medicaid matters: children's health and Medicaid eligibility expansions. *Journal of Policy Analysis and Management*, 21(2), 219-238.

Mann, C. (2002). The new Medicaid and CHIP waiver initiatives. Kaiser Commission on Medicaid and the Uninsured.

Miller, S., Johnson, N., & Wherry, L. R. (2021). Medicaid and mortality: new evidence from linked survey and administrative data. The Quarterly Journal of Economics, 136(3), 1783-1829.

O'Neill, S., Kreif, N., Sutton, M., & Grieve, R. (2020). A comparison of methods for health policy evaluation with controlled pre-post designs. Health services research, 55(2), 328-338.

Nolte E, McKee CM. In amenable mortality—deaths avoidable through health care—progress in the US lags that of three European countries. Health Aff (Millwood). 2012;31(9). Published online August 29, 2012

Rosenbaum, P. (2007). Interference Between Units in Randomized Experiments. *Journal of the American Statistical Association*, 191-200.

Sommers, B. D. (2017). State Medicaid expansions and mortality, revisited: a cost-benefit analysis. *American Journal of Health Economics*, *3*(3), 392-421.

Sommers, B. D., Baicker, K., & Epstein, A. (2012). Mortality and Access to Care among Adults after State Medicaid Expansions. *The New England Journal of Medicine*, 1025-1034.

Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Analysis*, *25*(1), 57-76.

Table 1. Changes in Medicaid Enrollment in Expanding States

State	Expansion Year	Expansion Details (% of FPL)			Medicaid beneficiaries per capita, 5 Years Before	Medicaid beneficiaries per capita, 5 Years After	PP Change from Before to After (%Δ)	Included by Sommers et al.?	Included by Us
		Pregnant women	Parents	Childless Adults					
Arizona	2001	-	200%	100%	.107	.174	.067*** (62.6)	Yes	Yes
Hawaii	1993	185%	100%	100%	.081	.067	.014 (17.3)	No	No
Illinois	2002	-	185%	185%	.115	.153	.038*** (33)	No	Yes
Maine	2002	(‘89-’93: 100%)	(‘89-’93: 100%)	100%	.142	.205	.063*** (44.4)	Yes	Yes
Massachusetts	2006	150% (free) 300% (subsidized)	150% (free) 300% (subsidized)	150% (free) 300% (subsidized)	.152	.185	.072*** (47.4)	No	No
Michigan	2004	-	-	35%	.116	.162	.046*** (39.7)	No	Yes
Minnesota	1992	-	185% (1993: 275%)	(1994: 125%)	.091	.093	.002 (2.2)	No	No
New Mexico	2005	200%	200%	200%	.20	.233	.037* (18.5)	No	Yes
New York	2001	-	150%	100%	.164	.203	.038*** (23.2)	Yes	Yes
Oregon	1994	100% (2002: 170%)	100% (2002: 185%)	100%	.094	.144	.05*** (53.2)	No	Yes

Rhode Island	2005	185-250%	185%	-	.161	.181	.019*** (11.8)	No	No
Tennessee	1994	400%	400%	400%	.151	.279	.128*** (84.8)	No	Yes
Utah	2002	150%	150%	150%	.71	.81	.01 (1.4)	No	No
Vermont	1995	150%	150%	150%	.134	.192	.058*** (43.3)	No	Yes
Washington	1993	-	-	200%	.101	.119	.017** (16.8)	No	No
Wisconsin	1999	(2008: 300%)	185%	(2008: 185%)	.088	.116	.028** (31.8)	No	No

Notes: * indicates 5-year change in percent of the population on Medicaid is statistically significant at the * 10% level, ** 5% level, *** 1% level. Dash indicates no expansion for that particular group; for pregnant women and parents, this means eligibility was already at least as generous as the new cutoff for childless adults even before the expansion.

Table 2: Nationwide Estimates of Medicaid Expansions' Effect on Adult Mortality Rates

	(1) All-cause	(2) Healthcare amenable	(3) Healthcare Non-amenable	(4) HIV
Difference-in-differences	-11.70	-2.384	-9.320	-2.102
	(15.55)	(2.169)	(13.67)	(4.567)
	[-43.078, 19.668]	[-6.761, 1.992]	[-36.904, 18.263]	[-11.404, 7.199]
Generalized synthetic control method	2.217	-0.240	4.270	1.493
	(8.990)	(1.960)	(8.464)	(3.413)
	[-15.403,19.837]	[-4.082, 3.602]	[-12.319,20.859]	[-5.196, 8.182]
Baseline mortality rate (per 100,000 adults)	358.986	45.419	313.567	12.126

Notes: Estimates based on a sample of eight Medicaid expansion states and a donor pool of 35 control states including the District of Columbia over 13 years pre- and 9 years post-expansion, including the expansion year. Demographic (% female, black, white, Hispanic, age cohort) and economic (educational attainment, marital status, unemployment rate, poverty rate, logarithm of income, in the DID estimates only logarithm of Medicaid beneficiaries) but omitted from presentation. Lower and upper bounds of 95% confidence intervals and standard errors reported in brackets and parentheses, respectively. Standard errors clustered at the state level in the DID models, obtained using parametric bootstrapping involving 1,000 bootstrap runs in the Generalized SCM models *** $p<0.01$, ** $p<0.05$, * $p<0$.

Table 3: State-Specific Estimates of Medicaid Expansions' Effect on All-Cause Adult Mortality Rate

	(1)	(2)	(3)	(4)
Panel A:	AZ	IL	ME	MI
Difference-in-differences	-5.940	-44.40***	12.17	8.994
	(7.543)	(7.737)	(7.737)	(8.099)
Synthetic control method	-10.595	-10.517	18.763	6.786
	[0.194]	[0.222]	[0.194]	[0.500]
Baseline mortality rate (per 100,000 adults)	344.402	352.859	311.433	347.978
	(5)	(6)	(7)	(8)
Panel B:	NM	NY	OR	VT
Difference-in-differences	40.55***	-98.90***	7.188	-5.893
	(8.263)	(7.543)	(5.858)	(6.285)
Synthetic control method	-1.080	-23.780	8.700	-9.432
	[0.684]	[0.750]	[0.750]	[0.694]
Baseline mortality rate (per 100,000 adults)	350.718	382.114	336.674	313.216

Notes: Estimates based on sample of one Medicaid expansion state and a donor pool of 35 control states including the District of Columbia and observations 13 years pre- and 9 years post-expansion. Demographic (% female, black, white, Hispanic, age cohort) and economic (educational attainment, marital status, unemployment rate, poverty rate, logarithm of income, logarithm of Medicaid beneficiaries) but omitted from presentation. Pseudo p-values based on permutation tests in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: State-Specific Estimates of Medicaid Expansions' Effect on Healthcare-Amenable Adult Mortality Rate

	(1)	(2)	(3)	(4)
Panel A:	AZ	IL	ME	MI
Difference-in-differences	1.009	-4.114***	-2.166	-0.828
	(1.366)	(1.381)	(1.381)	(1.392)
Synthetic control method	1.500	0.895	-0.285	2.221
	[0.917]	[0.639]	[0.611]	[0.167]
Baseline mortality rate (per 100,000 adults)	39.732	51.406	35.737	46.836
	(5)	(6)	(7)	(8)
Panel B:	NM	NY	OR	VT
Difference-in-differences	5.764***	-13.06***	0.107	-5.388***
	(1.418)	(1.366)	(1.146)	(1.171)
Synthetic control method	3.650	-3.232	0.207	-1.515
	[0.389]	[0.750]	[0.639]	[0.472]
Baseline mortality rate (per 100,000 adults)	39.505	54.447	38.927	37.323

Notes: Estimates based on sample of one Medicaid expansion states and a donor pool of 35 control states including the District of Columbia and observations 13 years pre- and 9 years post-expansion. Demographic (% female, black, white, Hispanic, age cohort) and economic (educational attainment, marital status, unemployment rate, poverty rate, logarithm of income, logarithm of Medicaid beneficiaries) but omitted from presentation. Pseudo p-values based on permutation tests in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: State-Specific Estimates of Medicaid Expansions' Effect on Healthcare Non-Amenable Adult Mortality Rate

	(1)	(2)	(3)	(4)
Panel A:	AZ	IL	ME	MI
Difference-in-differences	-6.948	-40.28***	14.33**	9.822
	(6.402)	(6.580)	(6.580)	(6.920)
Synthetic control method	-8.233	-9.835*	17.579	0.507
	[0.222]	[0.083]	[0.306]	[0.889]
Baseline mortality rate (per 100,000 adults)	304.67	301.453	275.696	301.141
	(5)	(6)	(7)	(8)
Panel B:	NM	NY	OR	VT
Difference-in-differences	34.78***	-85.84***	7.081	-0.505
	(7.055)	(6.402)	(4.912)	(5.317)
Synthetic control method	8.102	-20.630	9.814	-6.971
	[0.500]	[0.788]	[0.556]	[0.972]
Baseline mortality rate (per 100,000 adults)	311.213	327.667	297.747	275.893

Notes: Estimates based on sample of one Medicaid expansion states and a donor pool of 35 control states including the District of Columbia and observations 13 years pre- and 9 years post-expansion. Demographic (% female, black, white, Hispanic, age cohort) and economic (educational attainment, marital status, unemployment rate, poverty rate, logarithm of income, logarithm of Medicaid beneficiaries) but omitted from presentation. Pseudo p-values based on permutation tests in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: State-Specific Estimates of Medicaid Expansions' Effect on HIV Adult Mortality Rate

	(1)	(2)	(3)	(4)
Panel A:	AZ	IL	ME	MI
Difference-in-differences	2.032	1.442	-	4.461**
	(2.221)	(2.158)		(2.140)
Synthetic control method	-0.544	-0.391	-	-0.314
	[0.428]	[0.464]		[0.536]
Baseline mortality rate (per 100,000 adults)	10.904	12.198	-	7.386
	(5)	(6)	(7)	(8)
Panel B:	NM	NY	OR	VT
Difference-in-differences	4.341*	-22.60***	-0.370	-
	(2.160)	(2.221)	(1.363)	
Synthetic control method	0.183	-3.961	-1.621	-
	[0.643]	[0.321]	[0.250]	
Baseline mortality rate (per 100,000 adults)	6.717	43.4	9.561	-

Notes: Estimates based on sample of one Medicaid expansion states and a donor pool of 27 control states including the District of Columbia and observations 13 years pre- and 9 years post-expansion. Eight states were excluded due to missing values for HIV mortality in certain years, due to the confidentiality protocol of the Compressed Mortality Files, including expansion states ME and VT. OR analysis only includes 7 pre-expansion years as HIV outcomes available only after 1987 and OR expansion took place in 1994. Demographic (% female, black, white, Hispanic, age cohort) and economic (educational attainment, marital status, unemployment rate, poverty rate, logarithm of income, logarithm of Medicaid beneficiaries) but omitted from presentation. Pseudo p-values based on permutation tests in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 1: Generalized Synthetic Control Method Mortality Rate Trends in Treated and Synthetic States

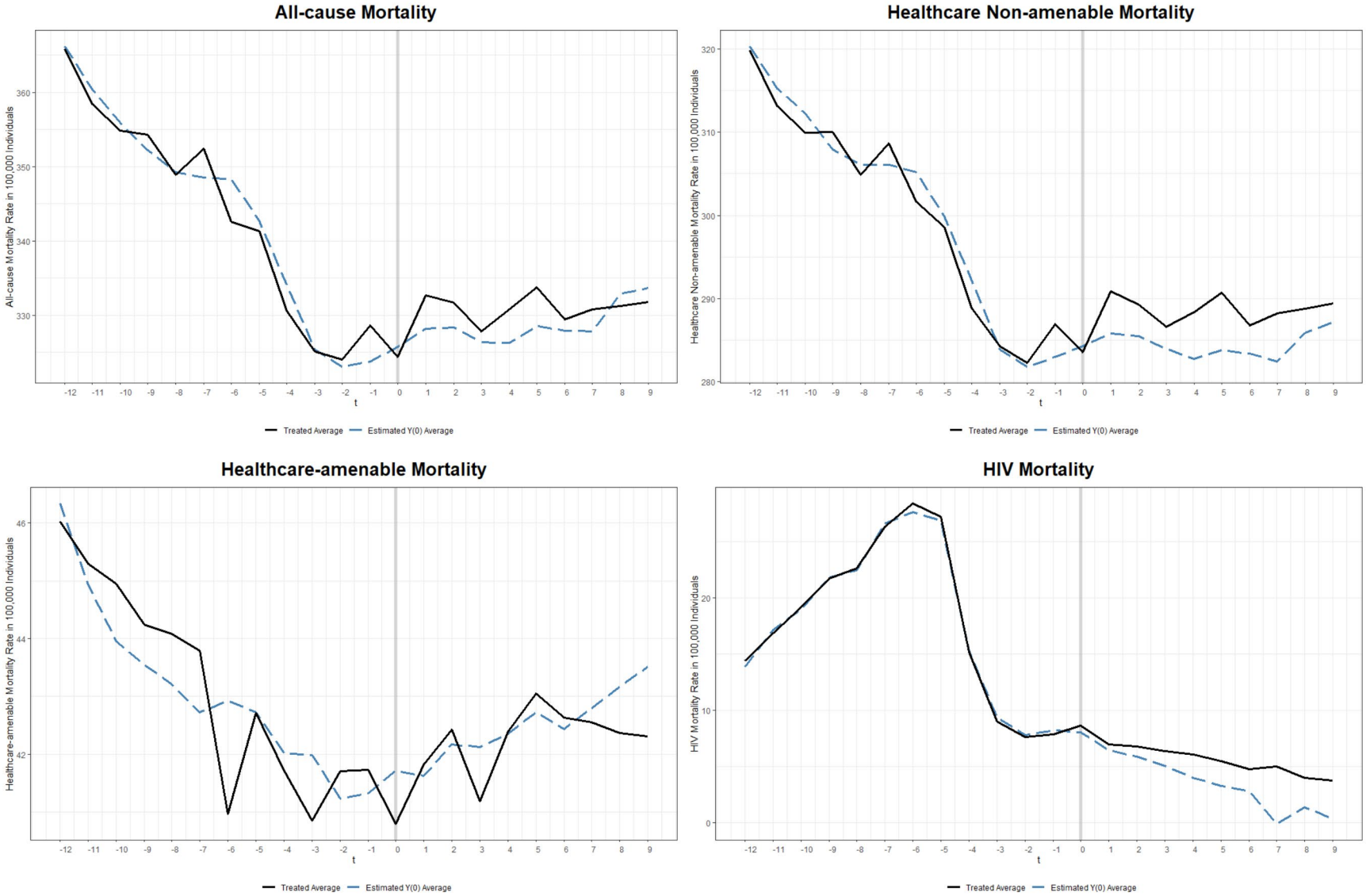
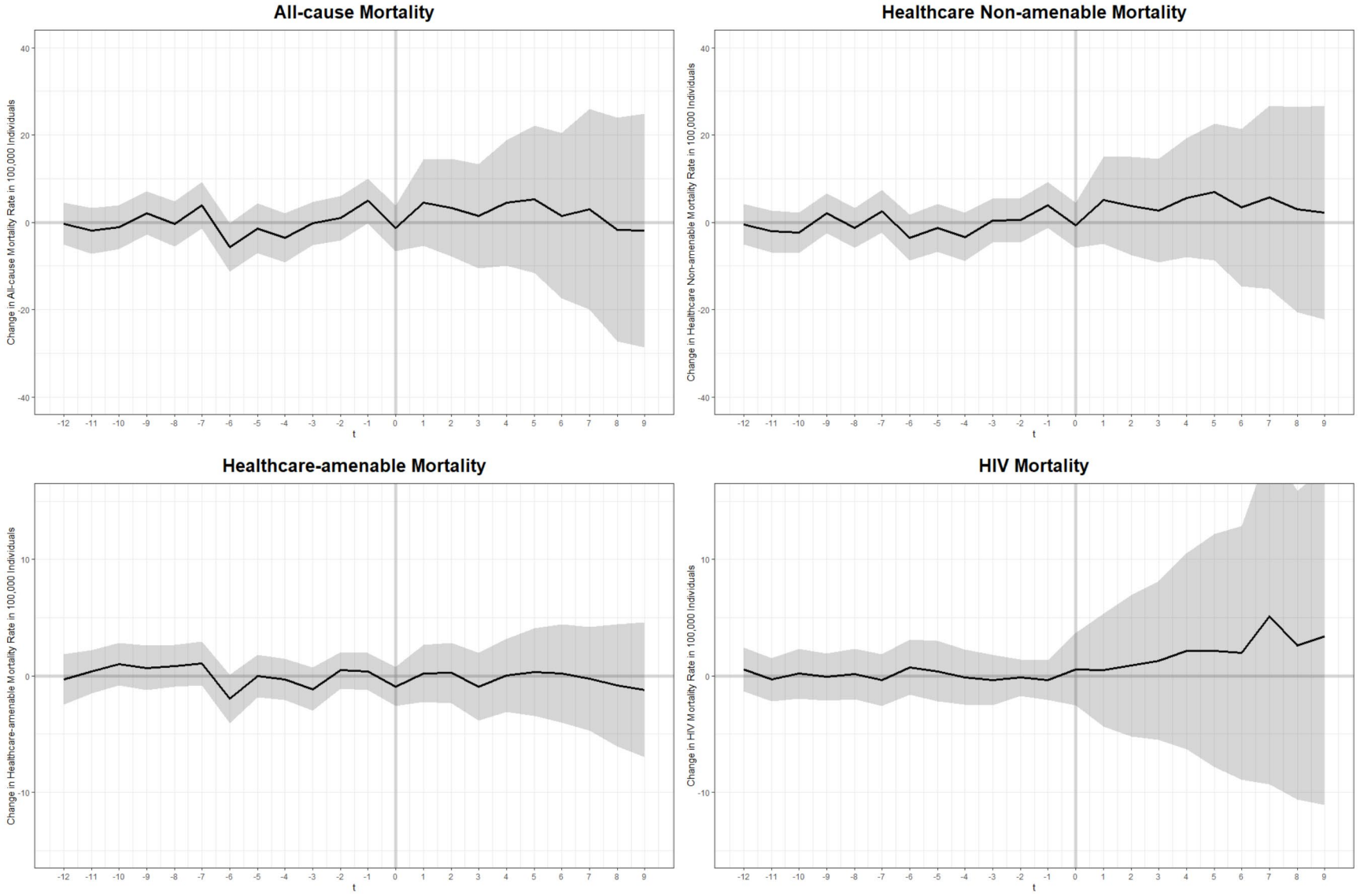


Figure 2: Generalized Synthetic Control Method Medicaid Expansions Effect on Mortality in Treated States



APPENDIX (online publication only)

A TABLES

Table A1: Summary Statistics

8 Medicaid Expansion States: AZ, IL, ME, MI, NM, NY, OR, VT; N = 108

VARIABLES	Mean	Std. Dev.	Min	Max
All-cause mortality rate	373.08	72.08	252.21	741.46
Healthcare-amenable mortality rate	49.26	13.79	23.63	128.4
Healthcare non-amenable mortality rate	323.82	59.72	222.08	643.62
HIV mortality rate	10.92	15.83	0.53	170.82
Total Medicaid beneficiaries	816,600.91	1,226,965	0	11,500,592
Medicaid beneficiaries per capita	0.13	0.05	0	0.38
% female	50.97	0.93	47.01	53.74
% black	12.73	12.7	0.21	70.73
% Hispanic	7.09	8.67	0.44	43.77
% white	83.3	12.46	27.96	99.29
% aged 20-34	22.82	3.07	17.26	33.67
% aged 35-44	14.33	1.77	9.6	20.11
% aged 45-54	12.01	2.19	8.45	17.16
% aged 55-64	9.51	1.58	5.13	14.68
% high school diploma	78.29	7.91	53.13	93.53
% married	56.58	5.01	27.14	65.86
Unemployment	6.16	2.16	2.3	17.8
Poverty	13.53	4.05	2.9	27.2
Average income	25,133.66	11,479.5	7,140.37	66,593.85

35 Medicaid Non-Expansion States: Rest of US excluding HI, MA, MN, TN, RI, UT, WA, WI; N=1,354

VARIABLES	Mean	Std. Dev.	Min	Max
All-cause mortality rate	326.16	33.92	264.73	406.69
Healthcare-amenable mortality rate	40.47	7.18	25.01	52.21
Healthcare non-amenable mortality rate	285.69	30.49	236.71	359.07
HIV mortality rate	4.63	3.92	1.24	17.37
Total Medicaid beneficiaries	1251034	1354595	99,693	5421241
Medicaid beneficiaries per capita	0.19	0.04	0.1	0.3
% female	50.83	0.41	50.09	51.77
% black	6.77	6.75	0.5	18.39
% Hispanic	13.34	13.16	0.78	47.31
% white	87.66	8.21	71.81	98.39
% aged 20-34	19.71	1.36	16.83	21.64
% aged 35-44	14.1	1.48	11.61	17.39
% aged 45-54	14.61	1.13	12.44	16.63
% aged 55-64	11.38	1.87	7.87	15.32
% high school diploma	86.03	2.89	79.64	91.85
% married	52.59	2.87	46.58	58.46
Unemployment	6.44	2.19	2.8	13.7
Poverty	13.34	3.06	7.6	22.2
Average income	35,572.69	6,653.56	21,635.75	54,447.38

Sources: CDC, Census, Bureau of Labor Statistics, National Cancer Institute

B FIGURES

Figure B1: SCM AZ all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

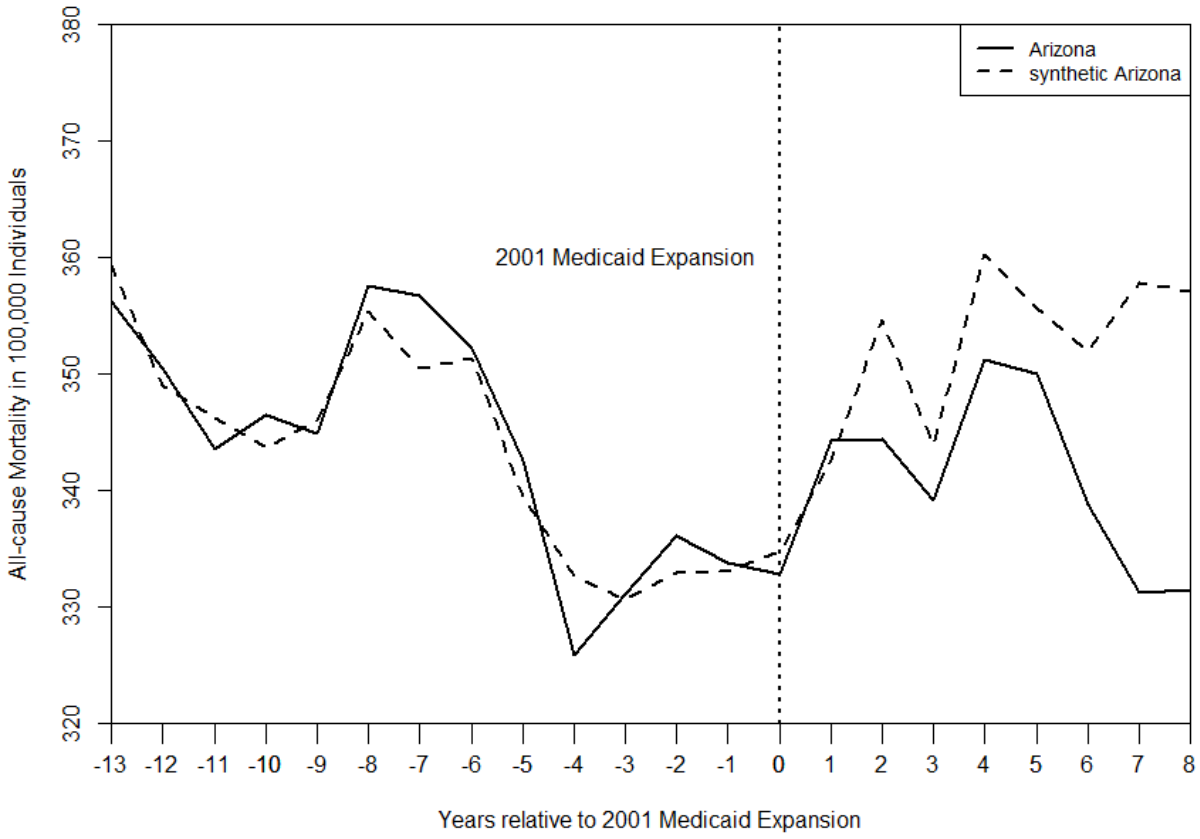


Figure B2: SCM AZ all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

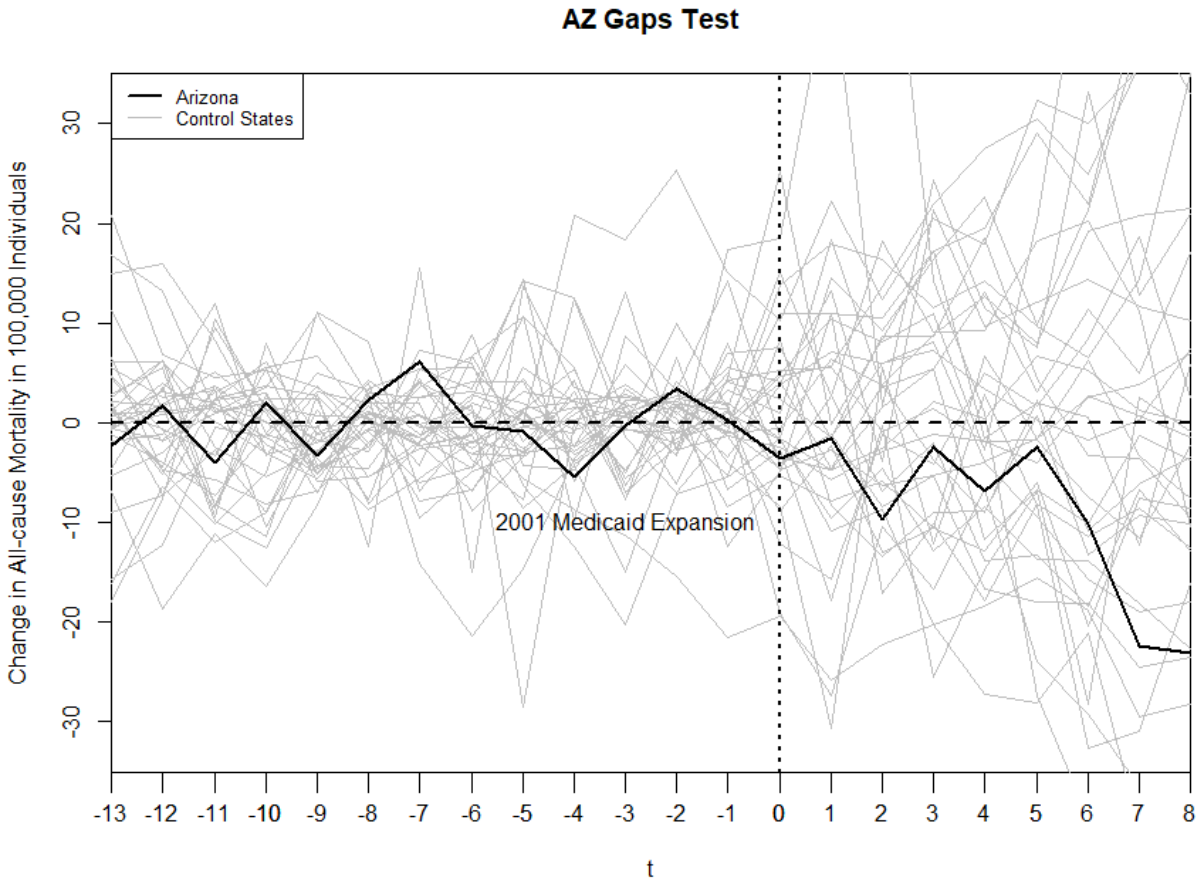


Figure B3: SCM IL all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

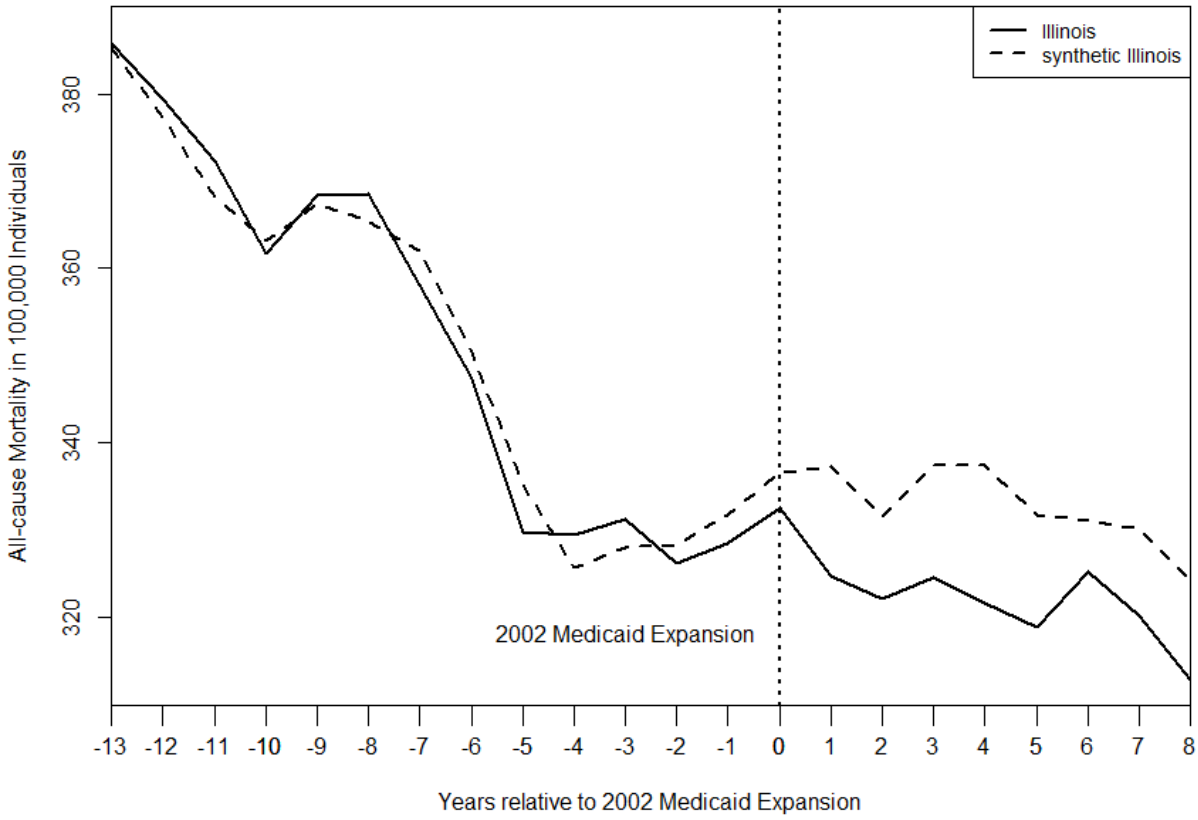


Figure B4: SCM IL all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

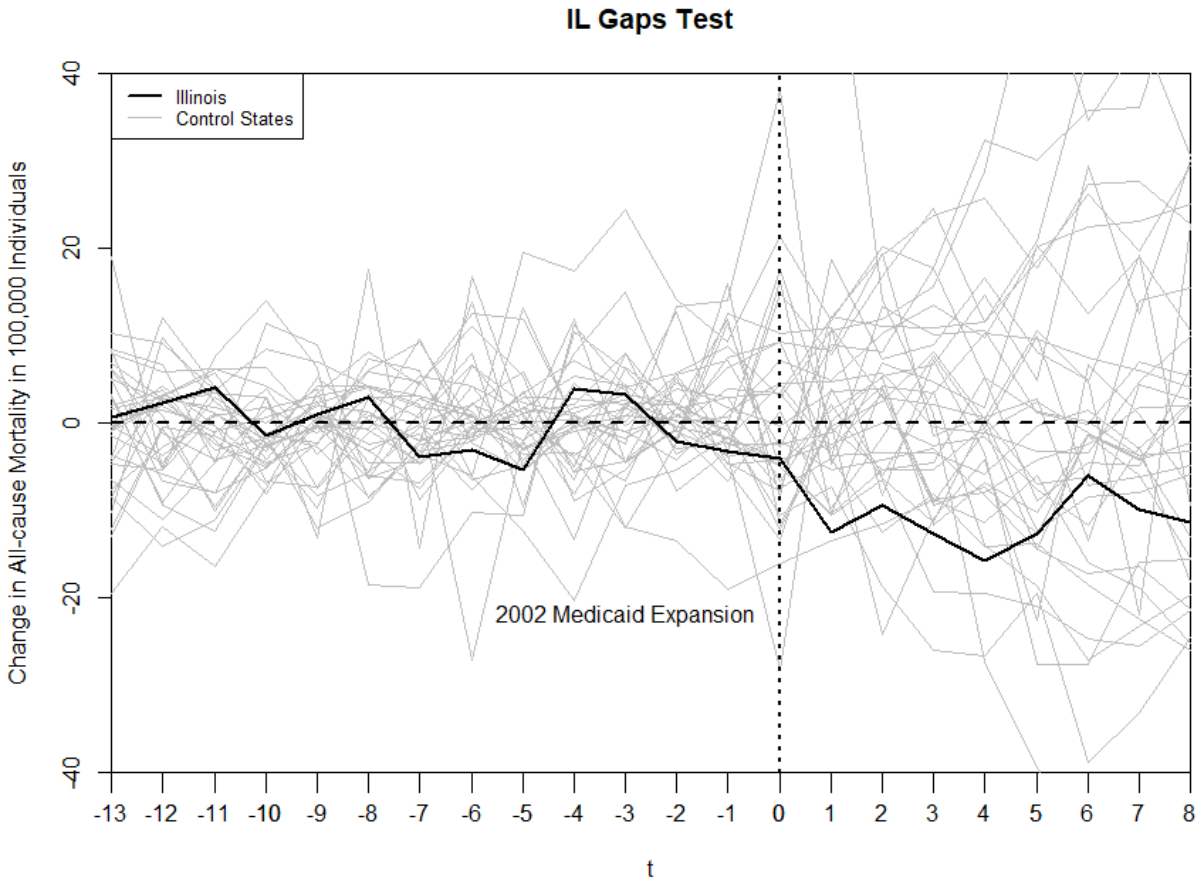


Figure B5: SCM ME all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

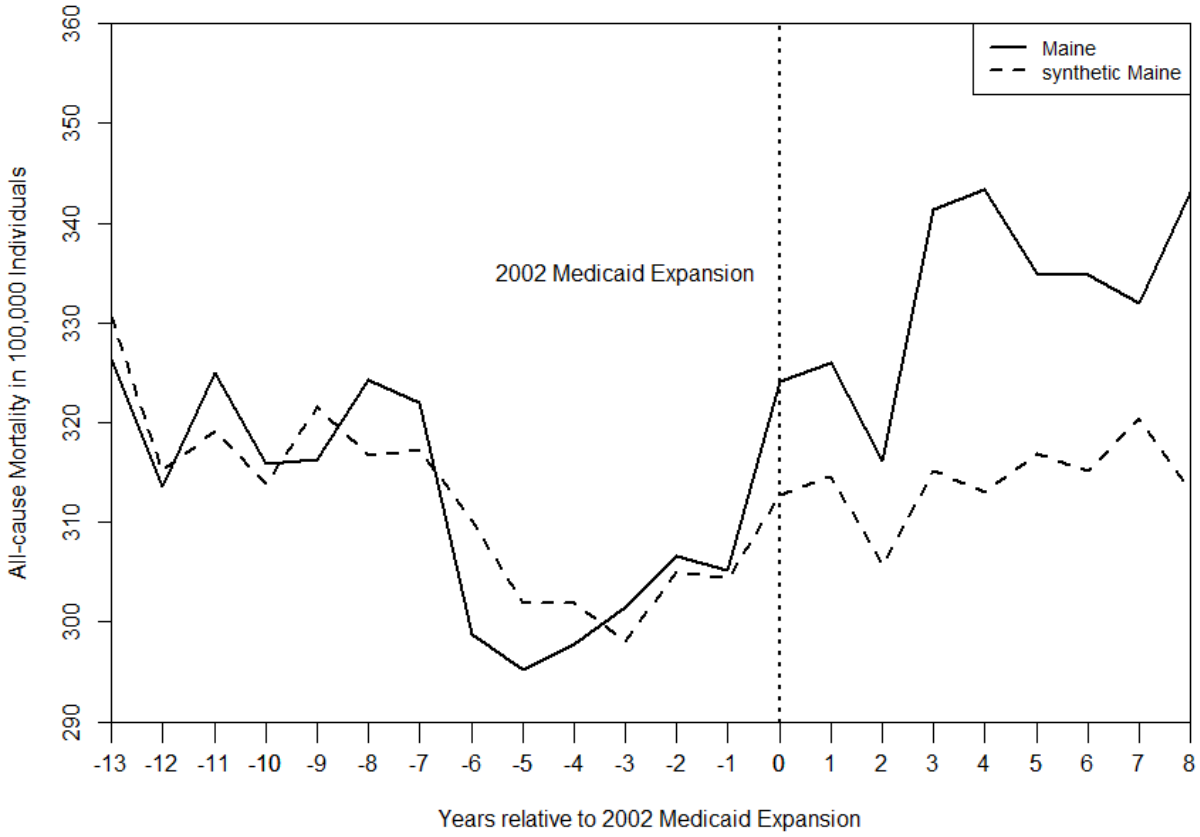


Figure B6: SCM ME all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

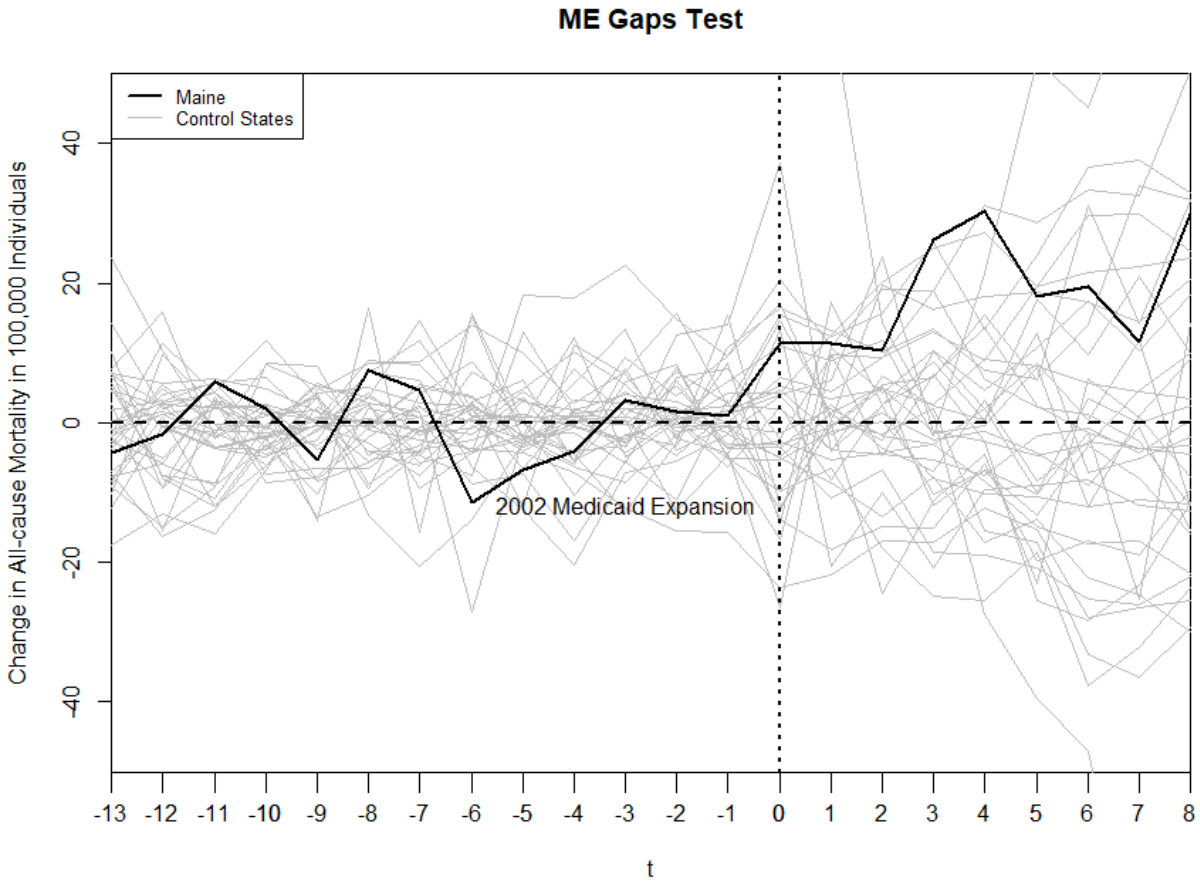


Figure B7: SCM MI all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

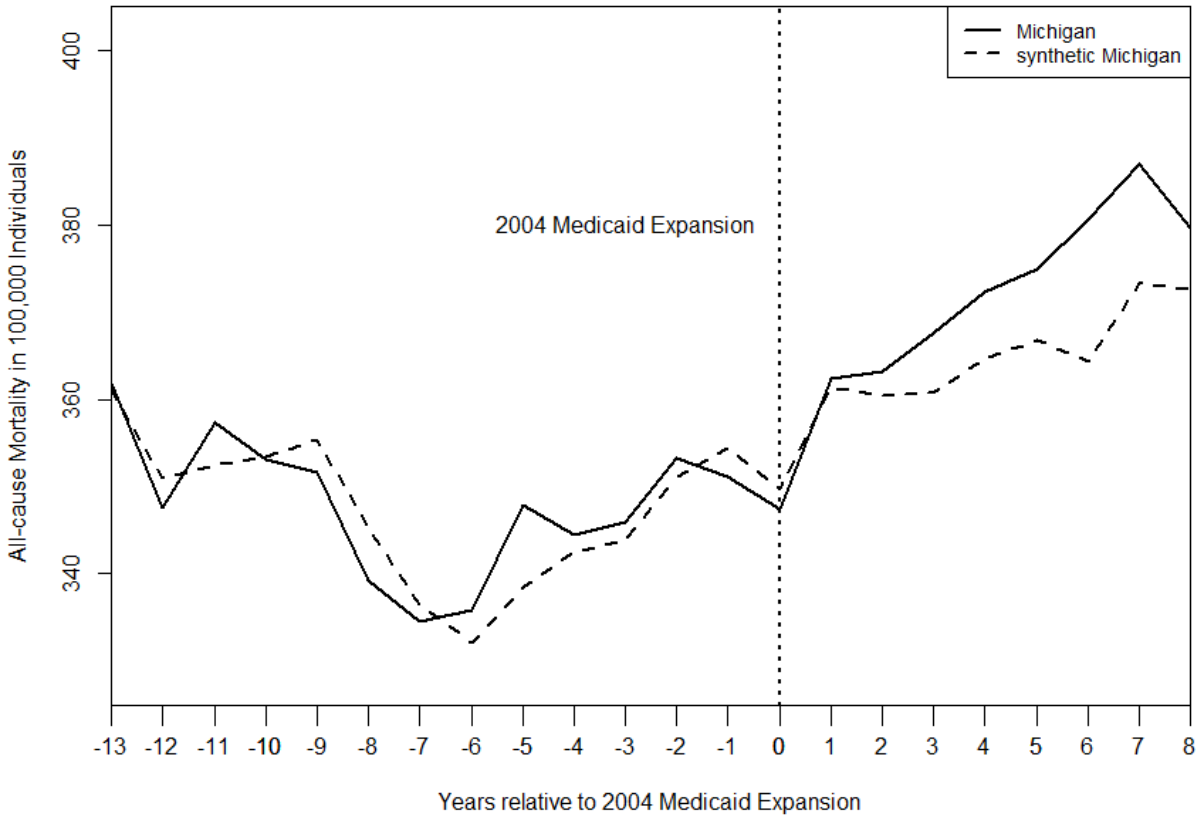


Figure B8: SCM MI all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

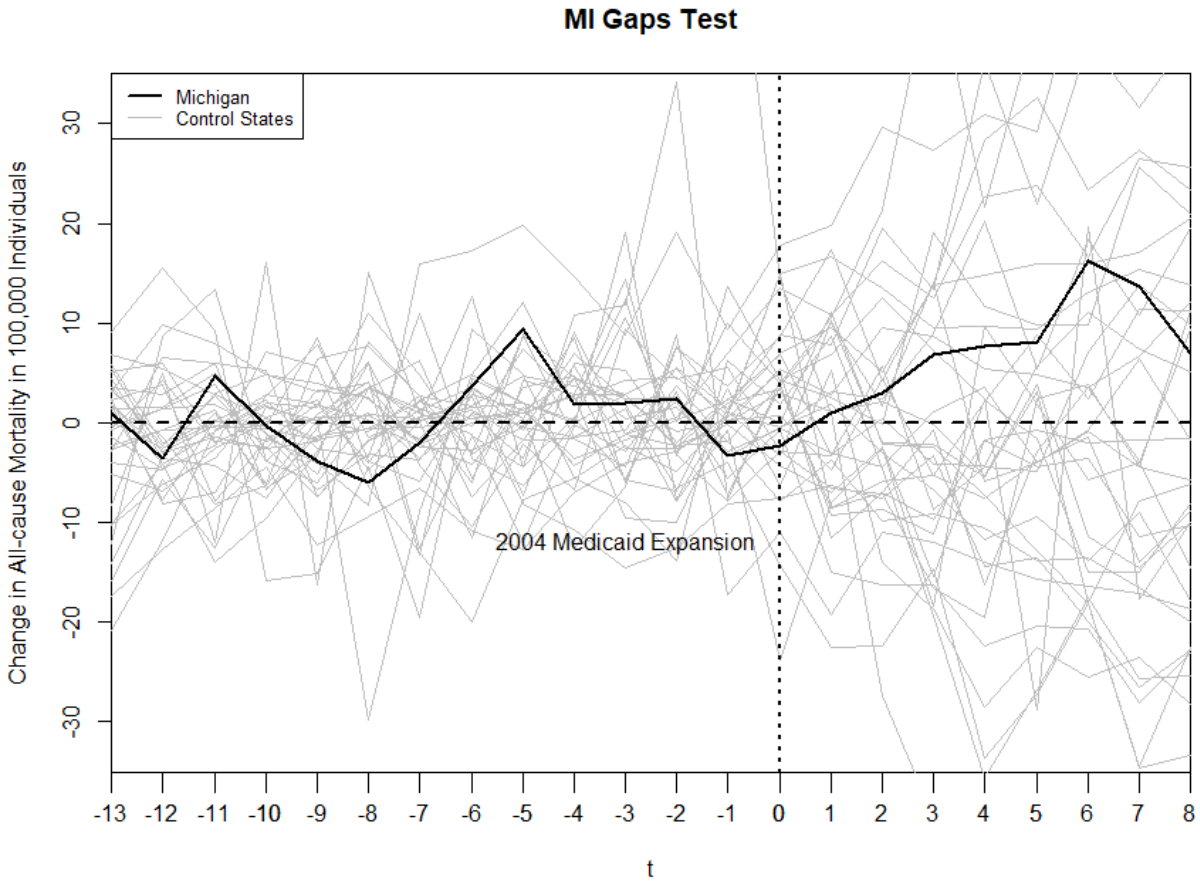


Figure B9: SCM NM all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

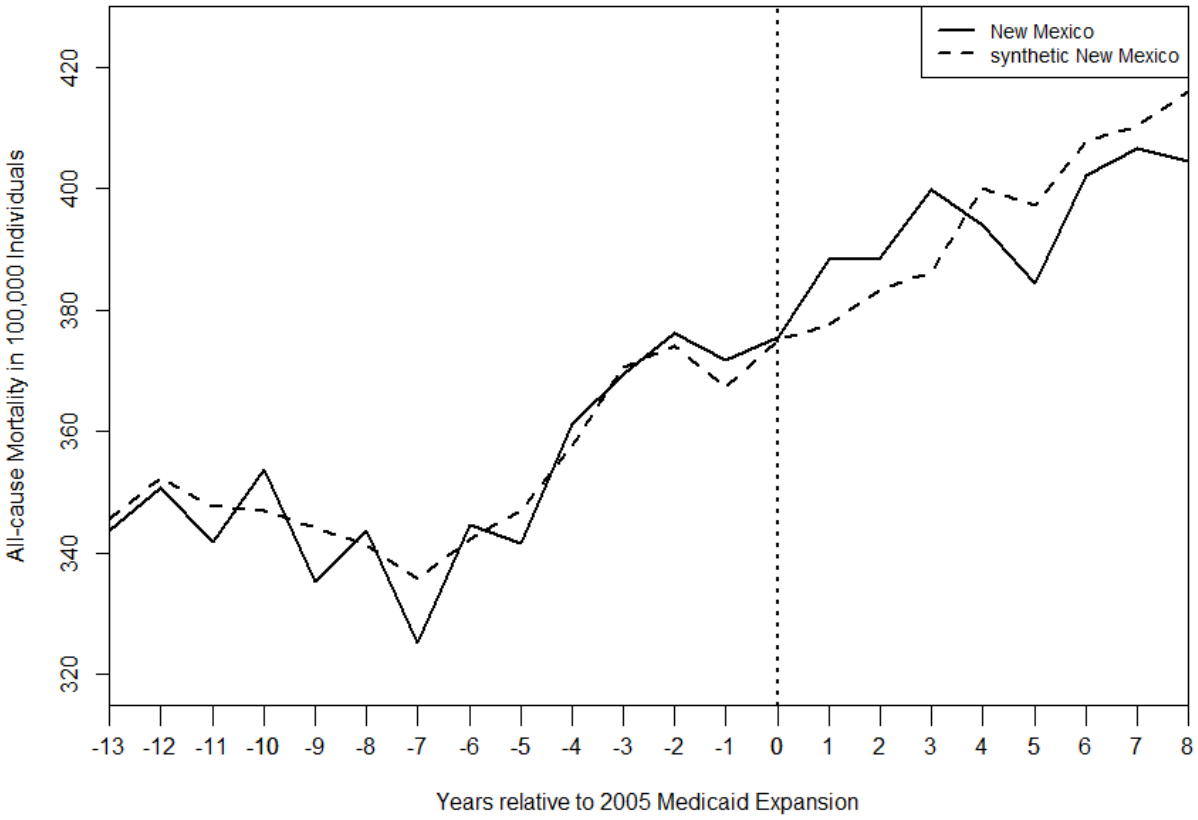


Figure B10: SCM NM all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

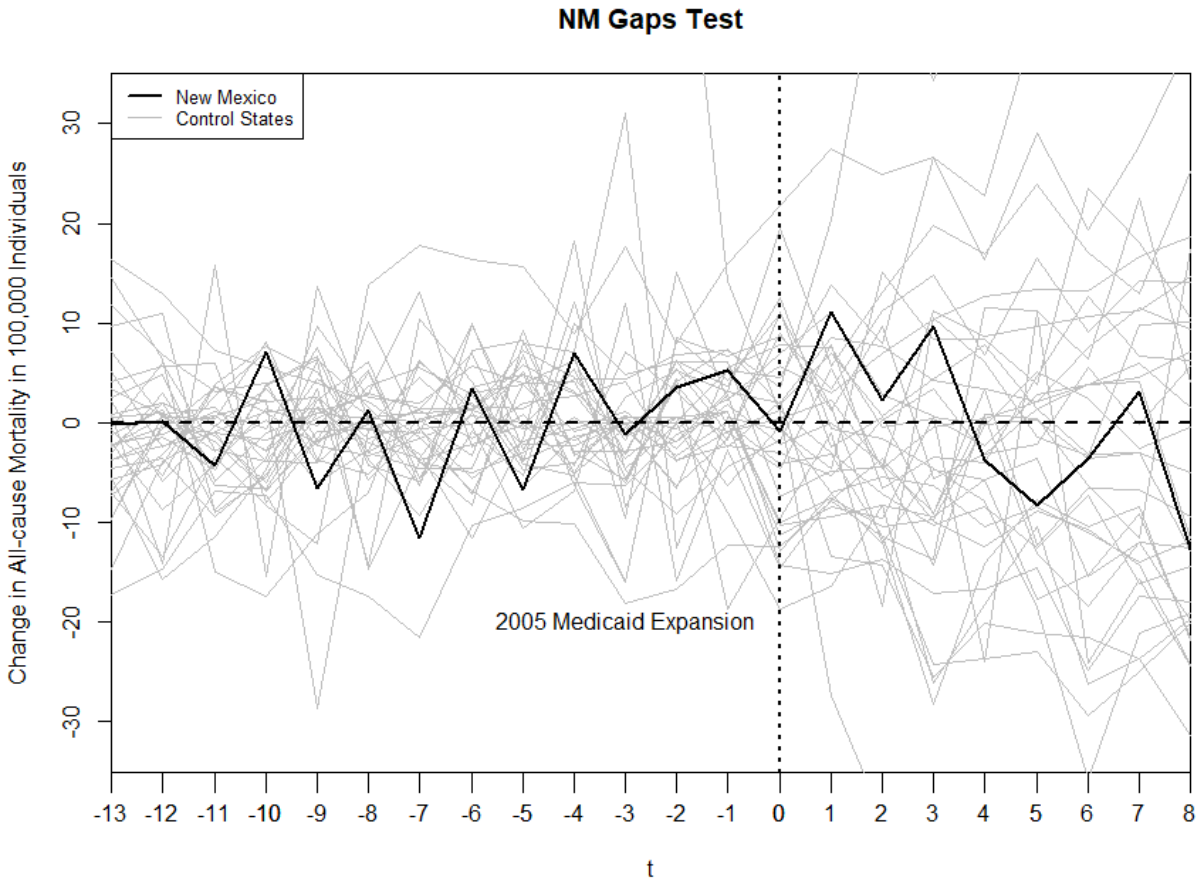


Figure B11: SCM NY all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

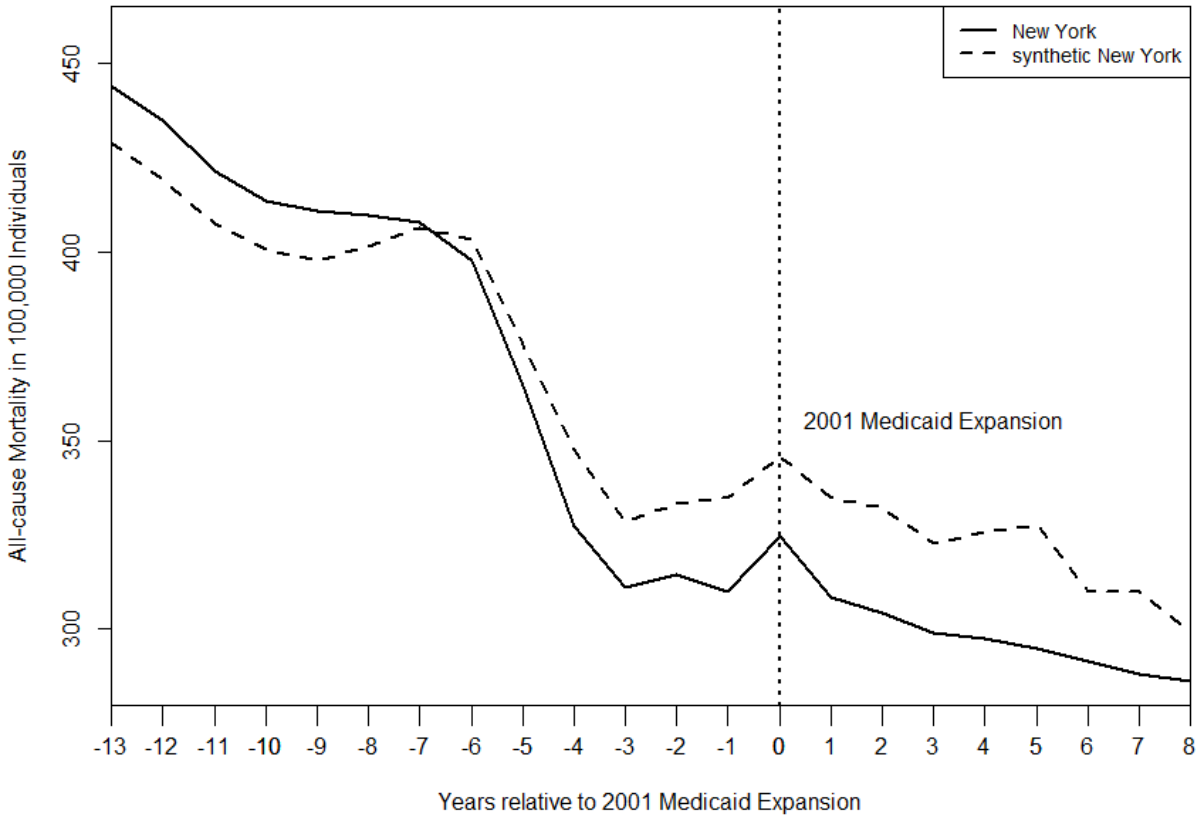


Figure B12: SCM NY all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

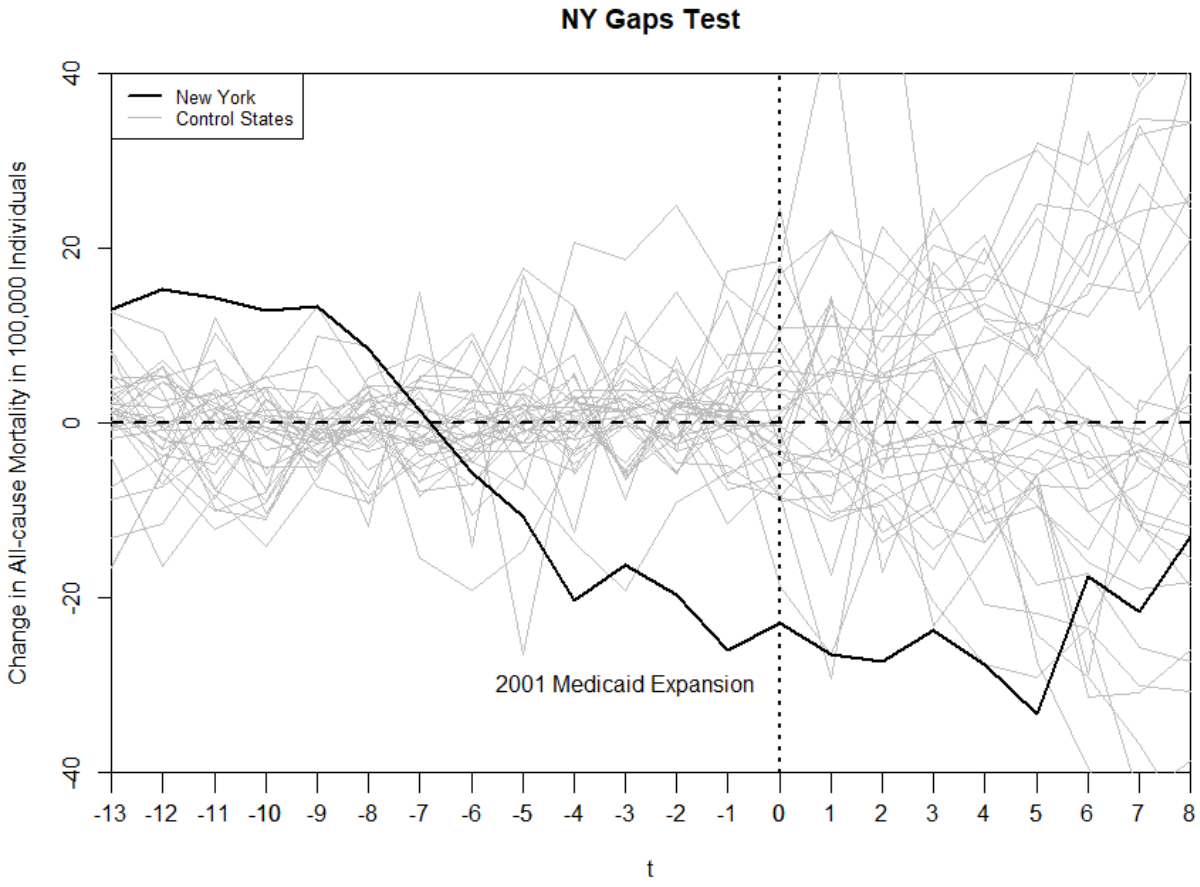


Figure B13: SCM OR all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

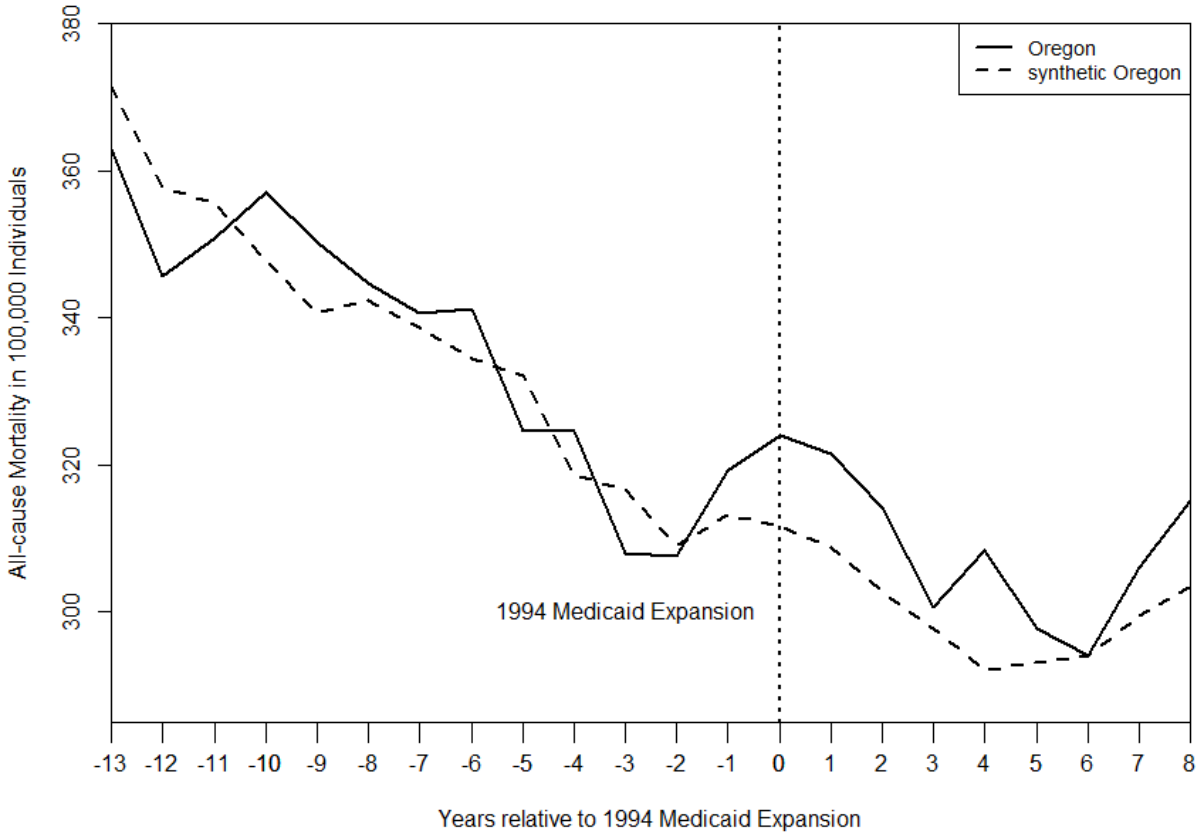


Figure B14: SCM OR all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

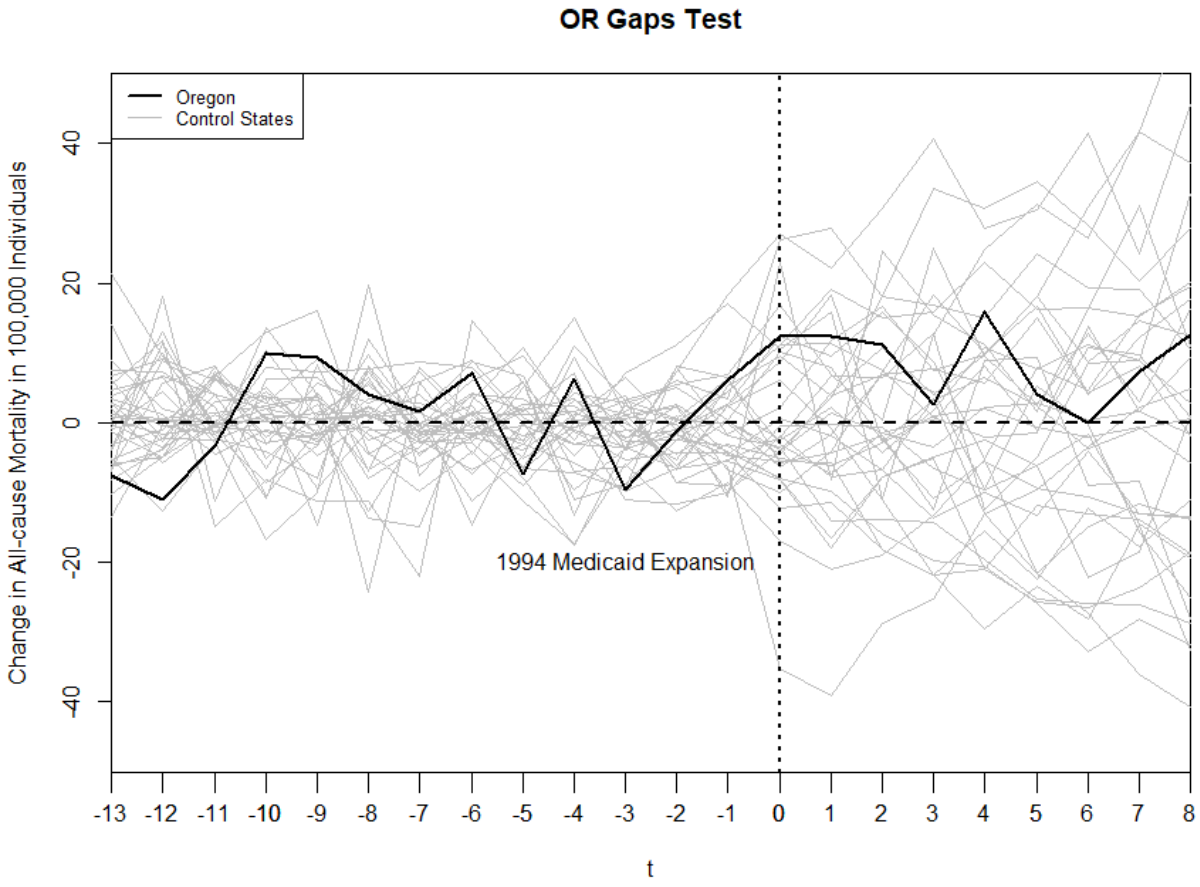


Figure B15: SCM VT all-cause mortality rate trends plot, 13 pre- and 8 post-treatment years

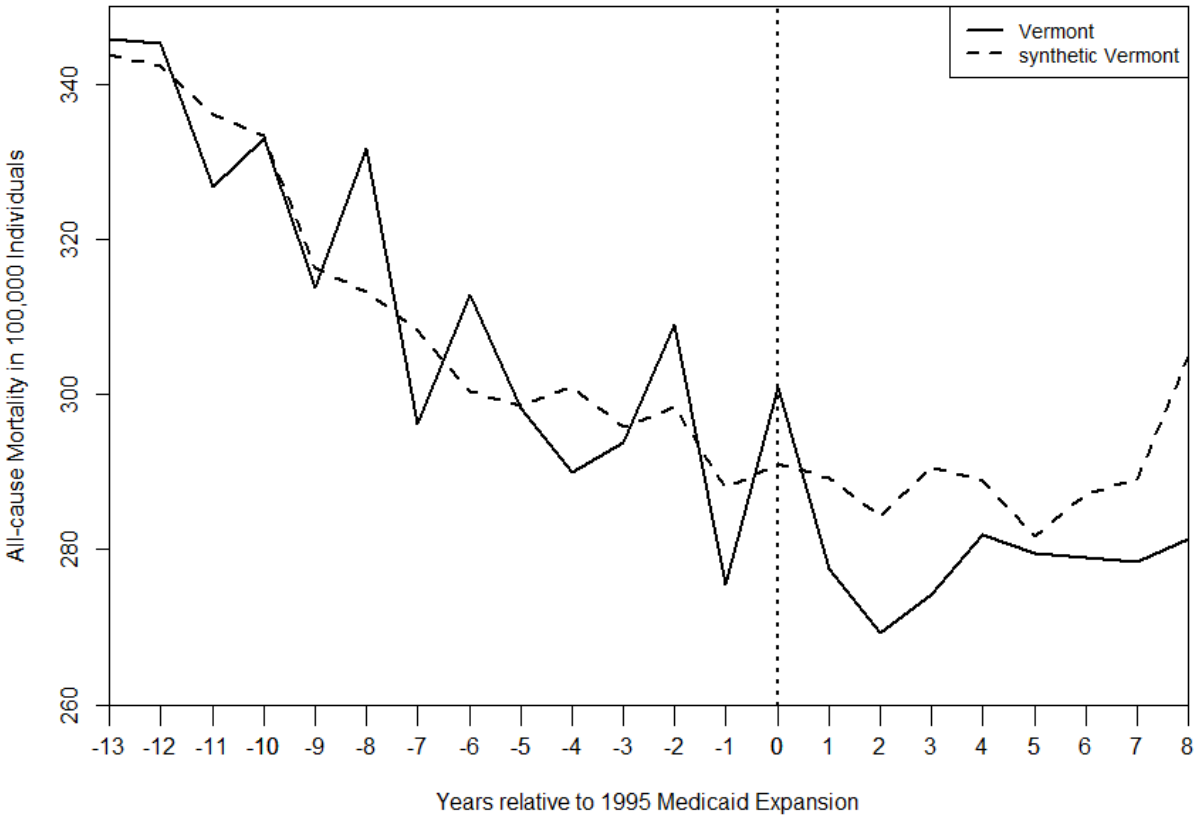


Figure B16: SCM VT all-cause mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

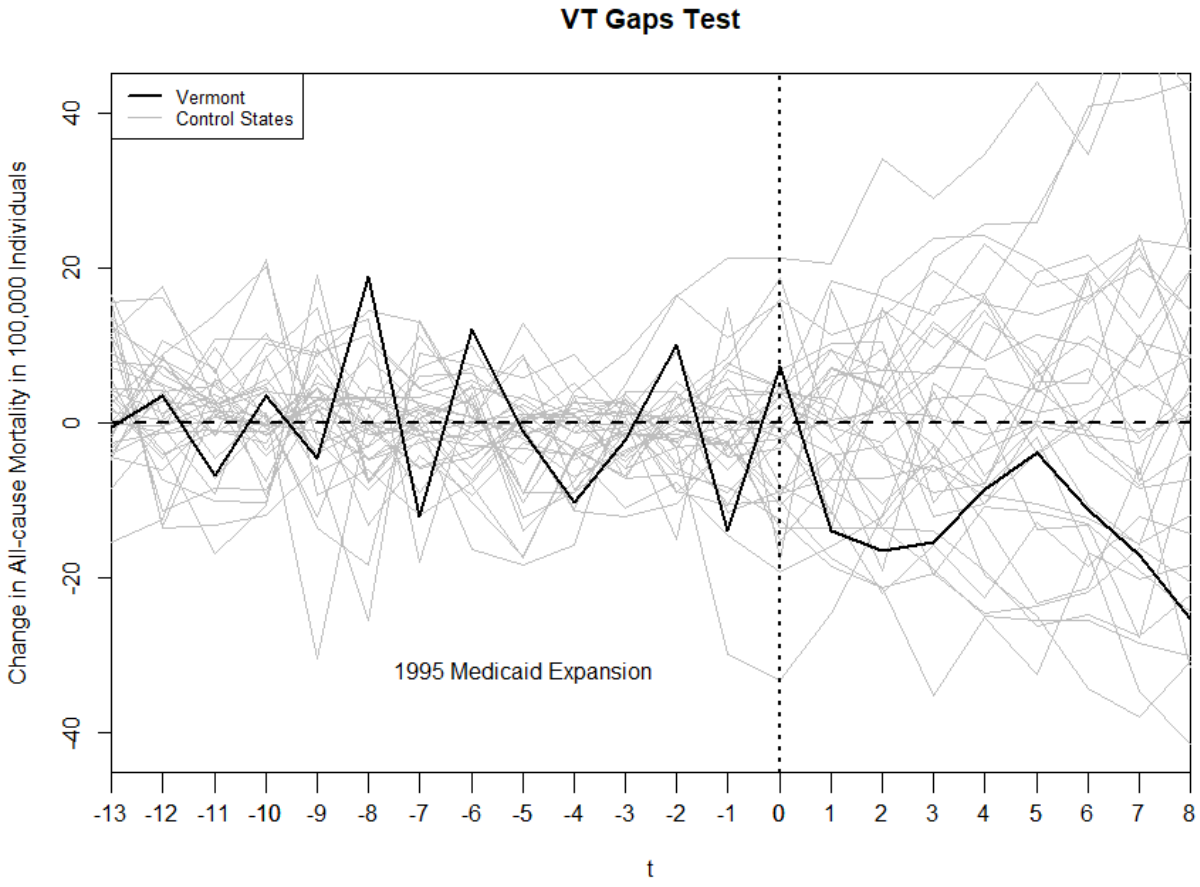


Figure B17: SCM AZ healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

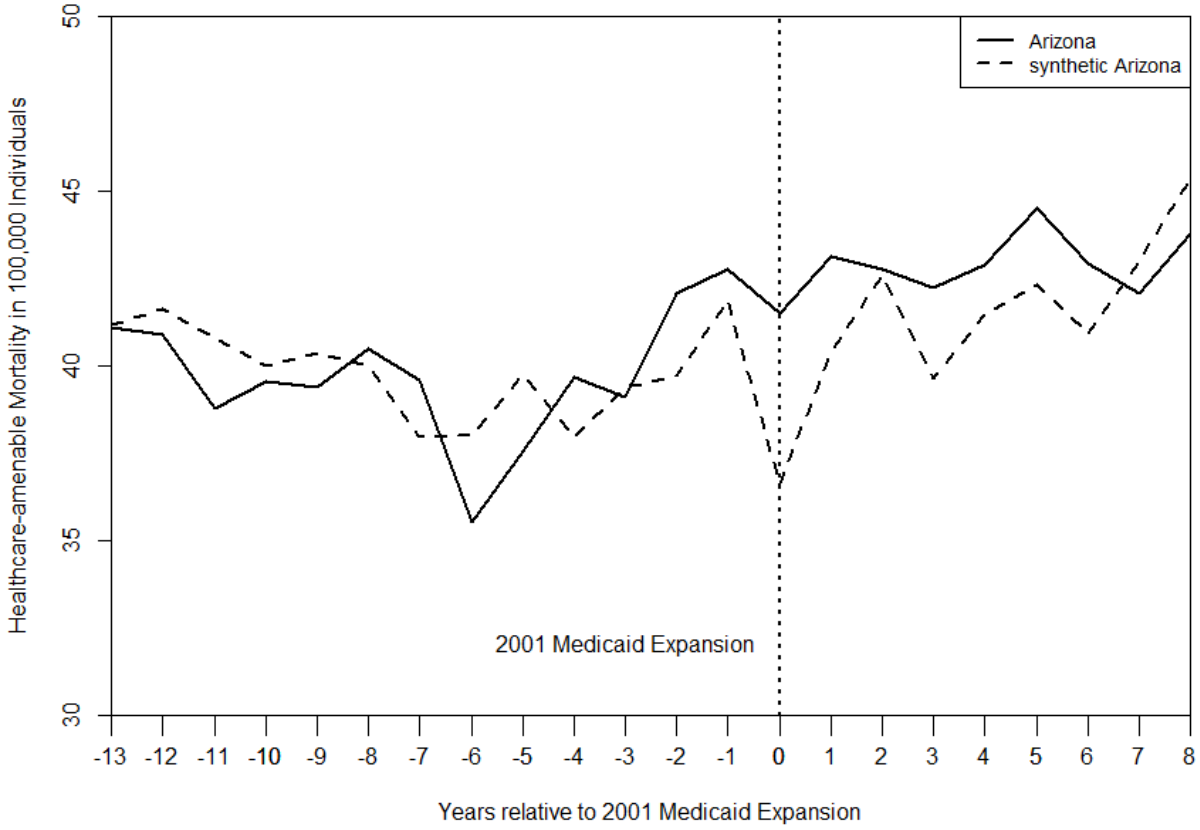


Figure B18: SCM AZ healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

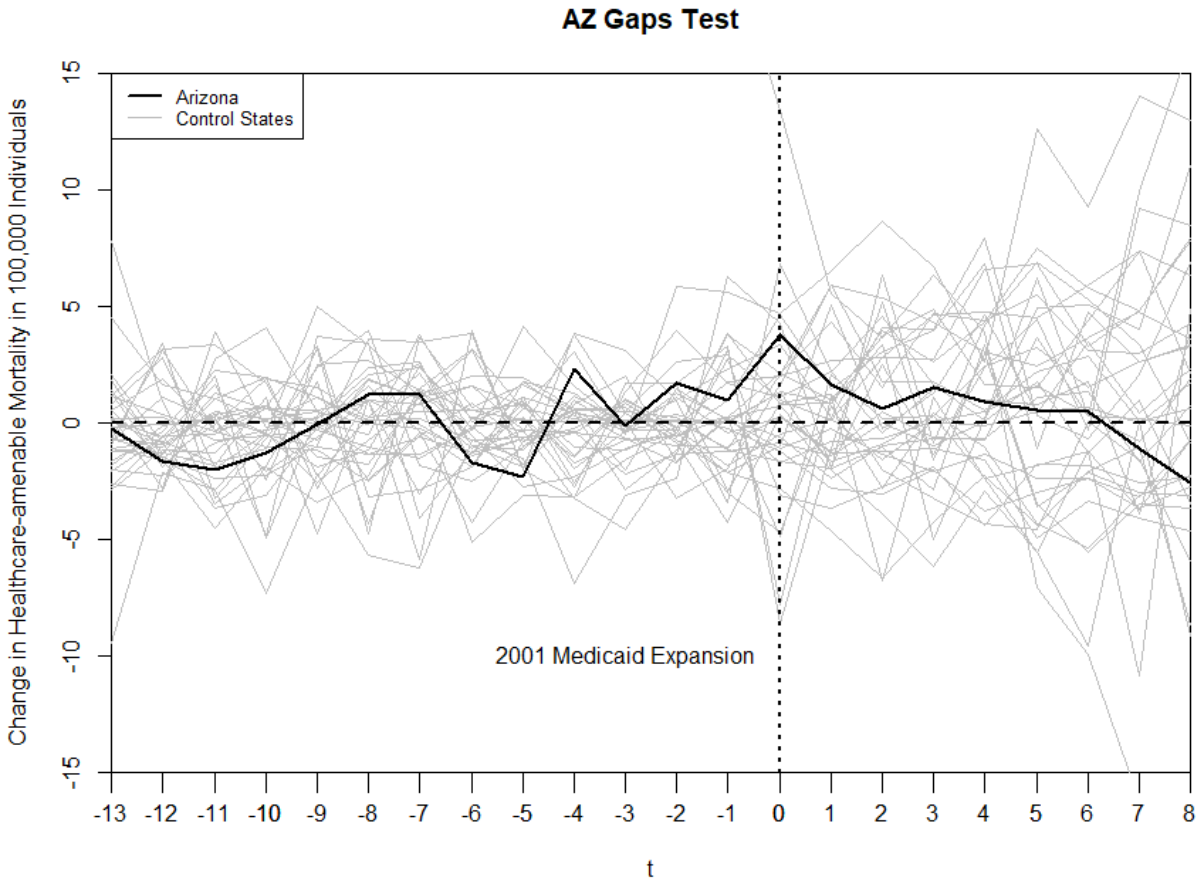


Figure B19: SCM IL healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

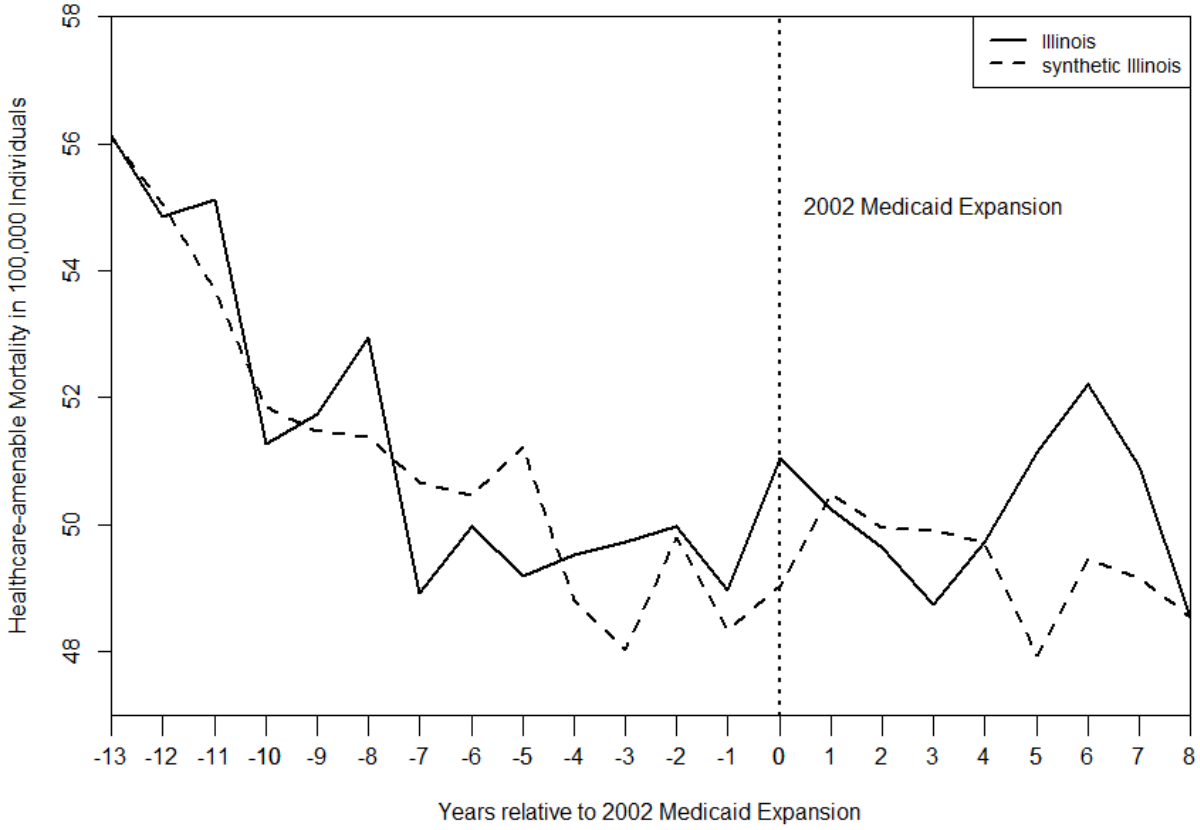


Figure B20: SCM IL healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

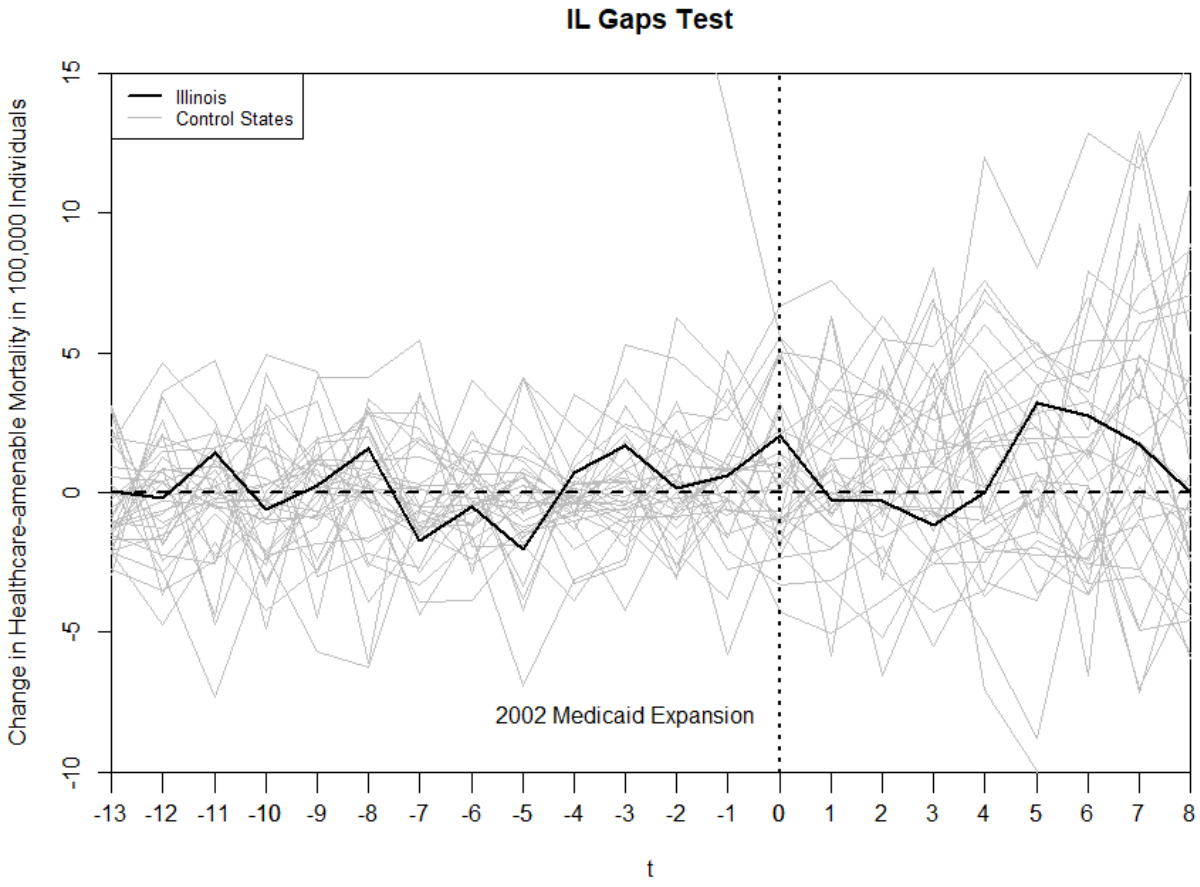


Figure B21: SCM ME healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

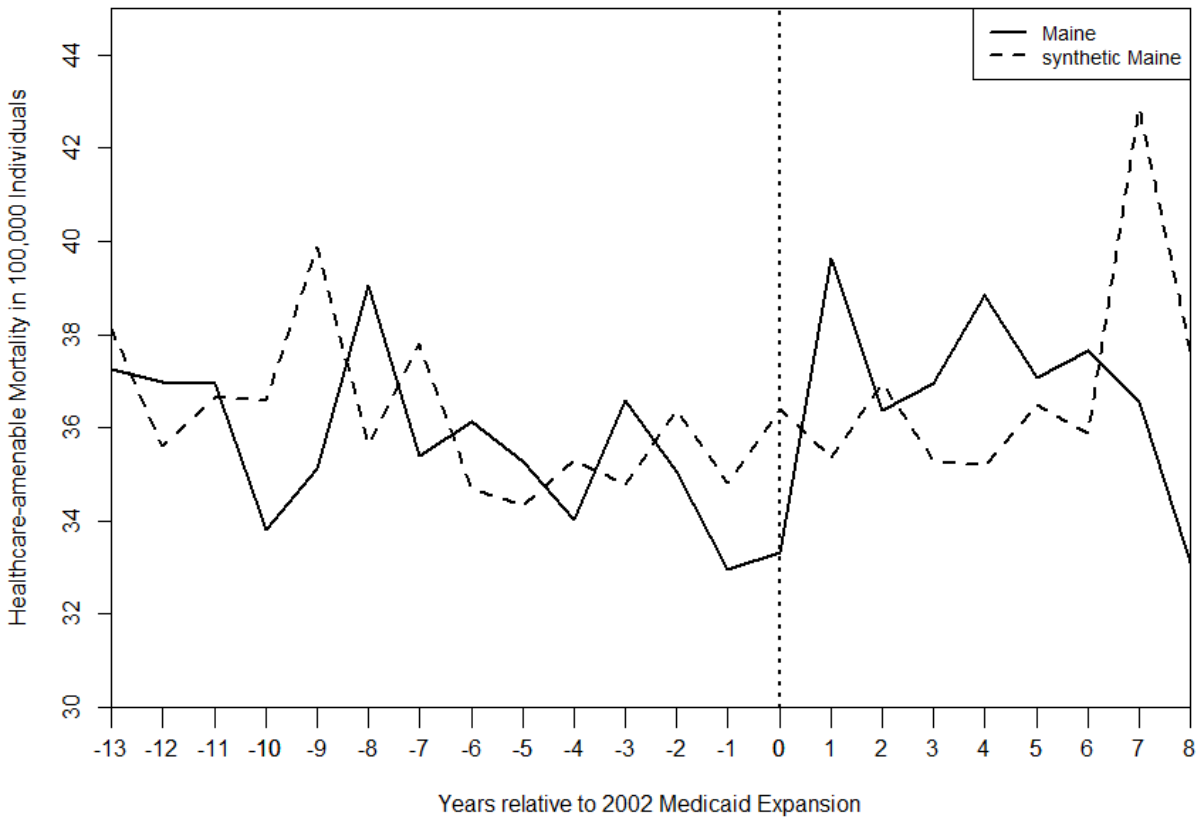


Figure B22: SCM ME healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

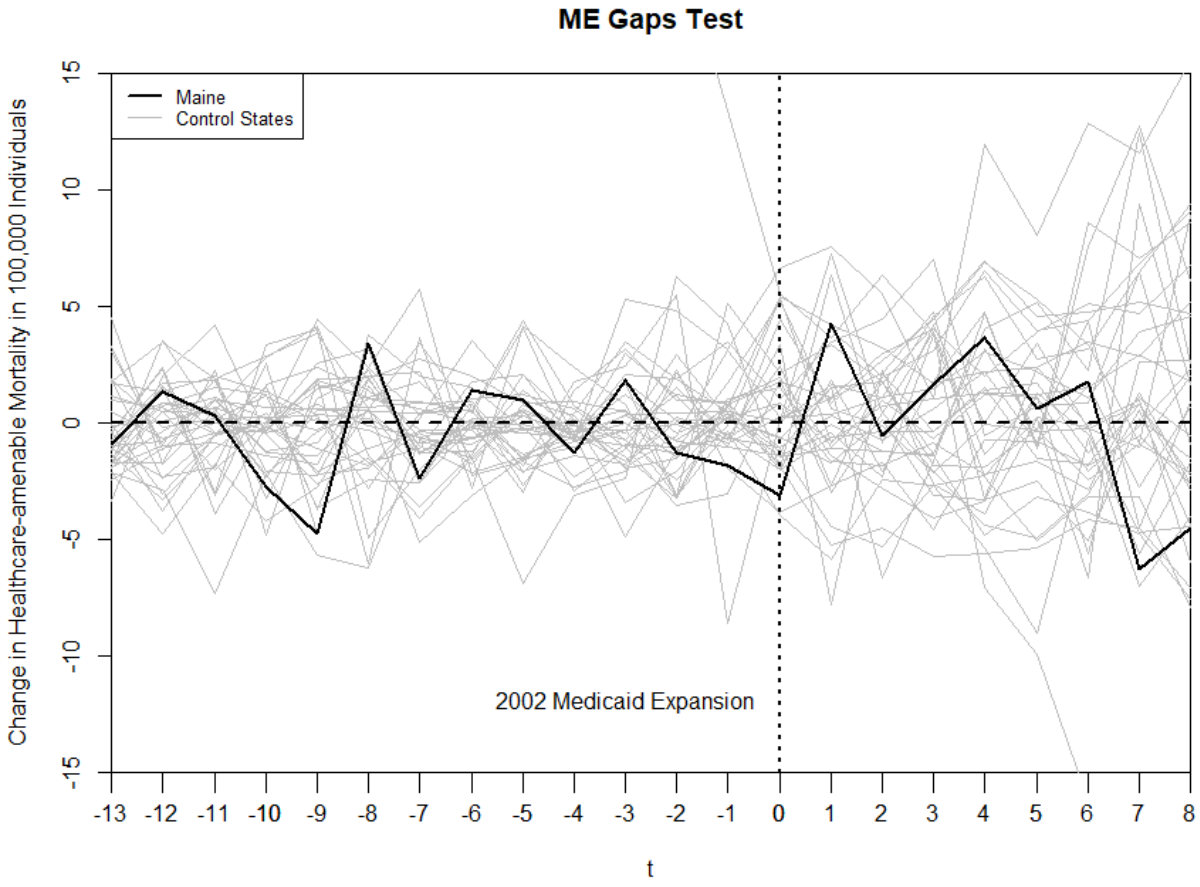


Figure B23: SCM MI healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

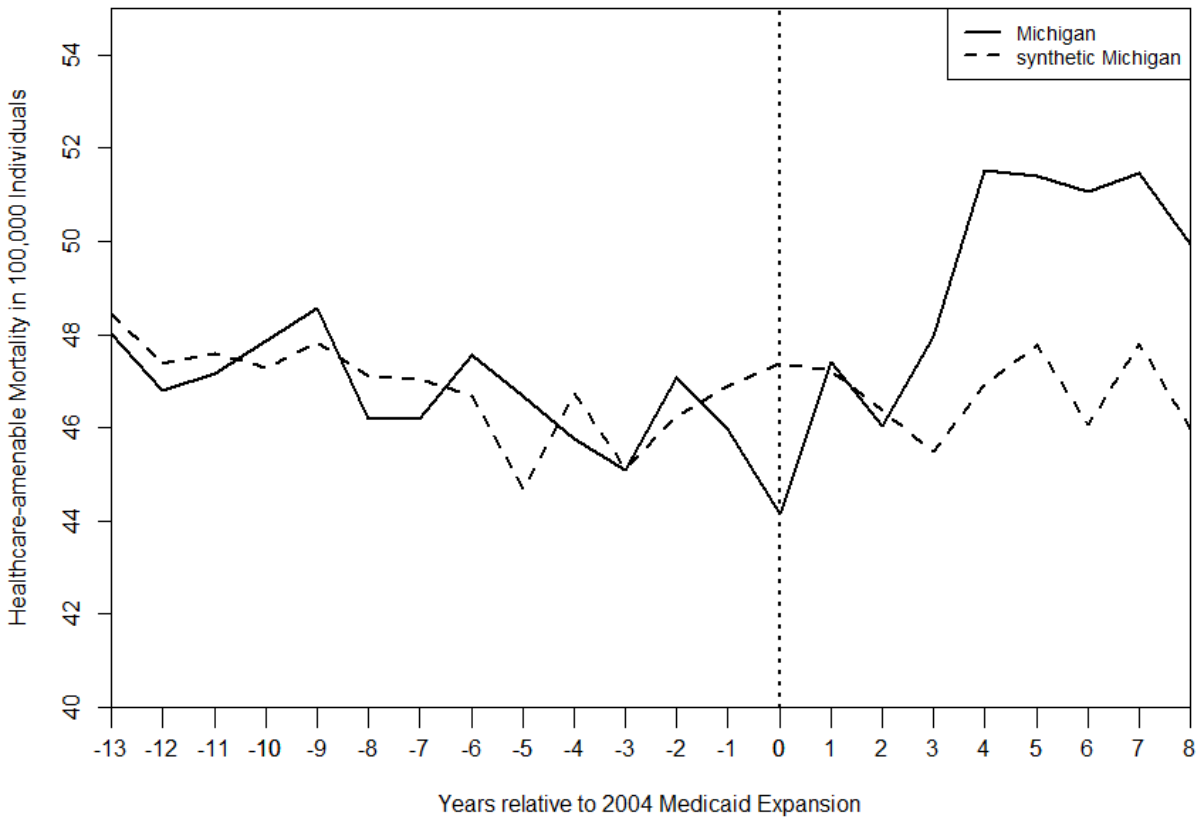


Figure B24: SCM MI healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

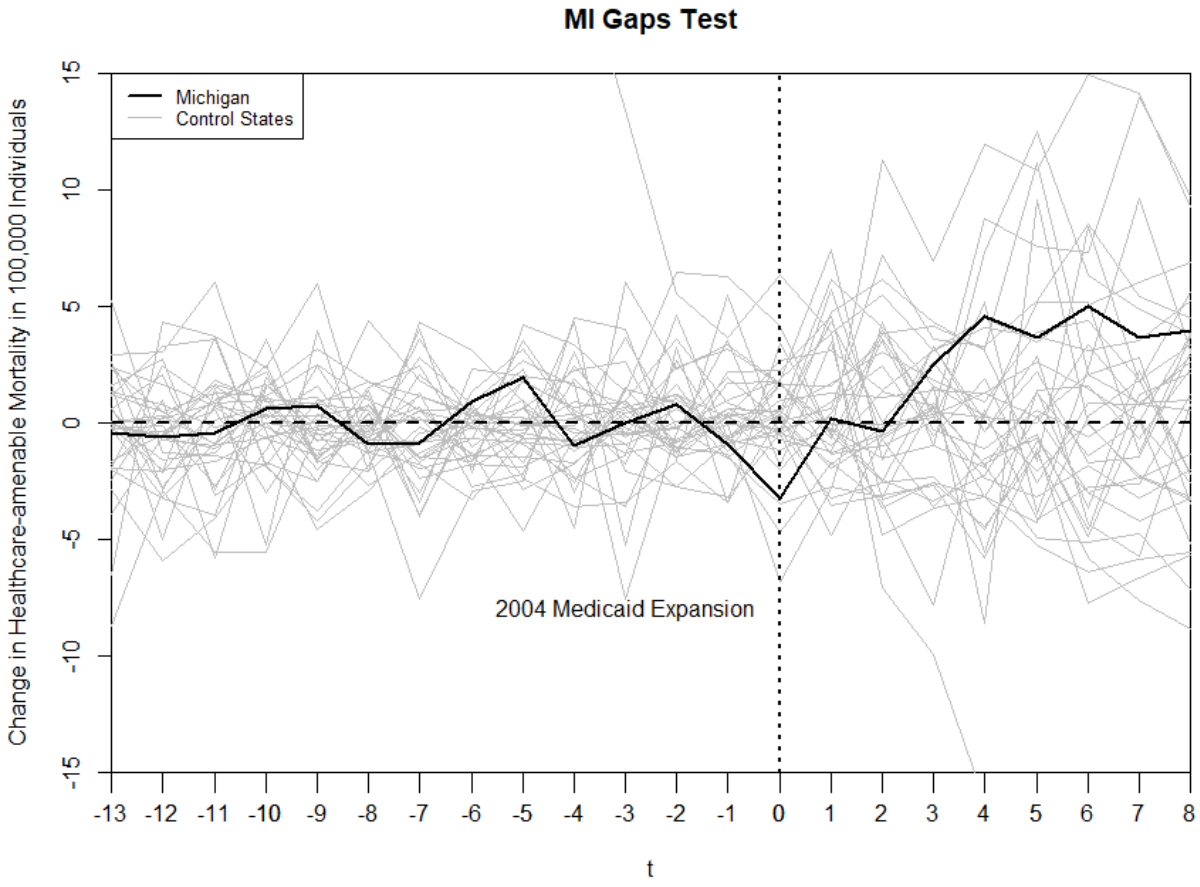


Figure B25: SCM NM healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

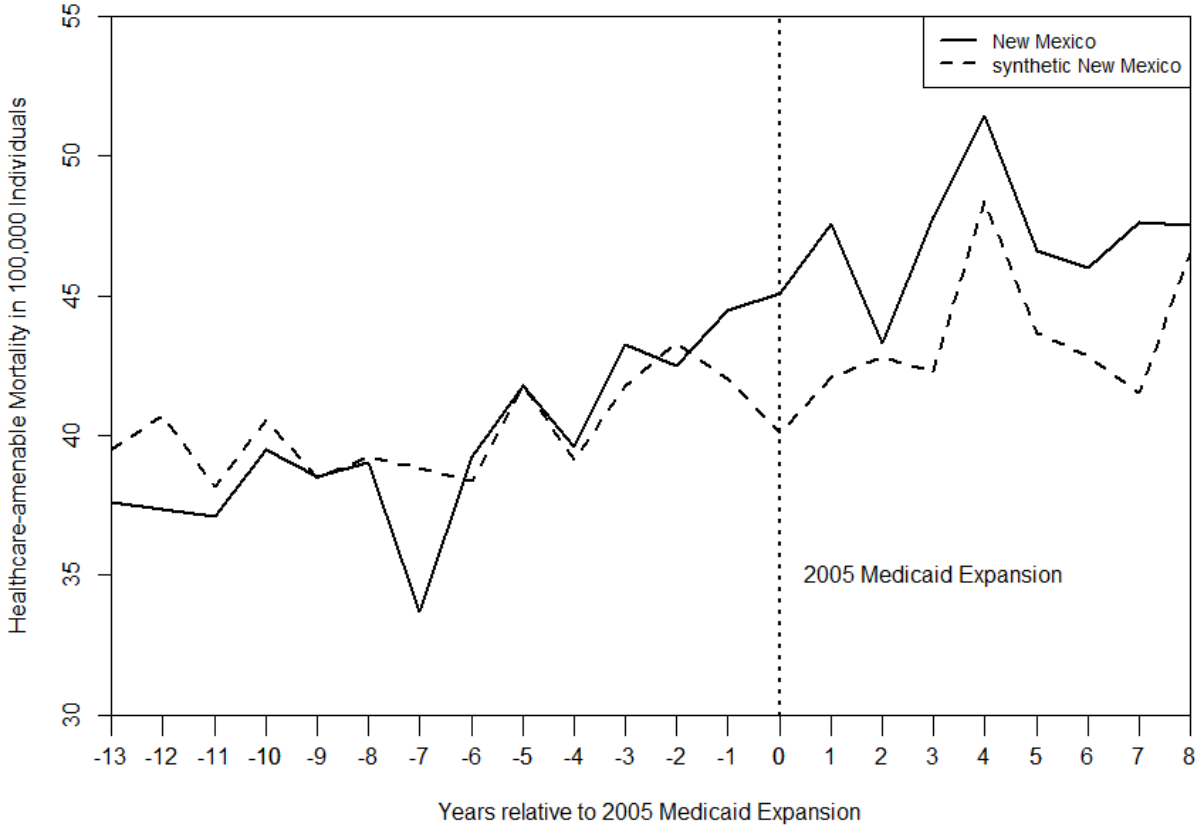


Figure B26: SCM NM healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

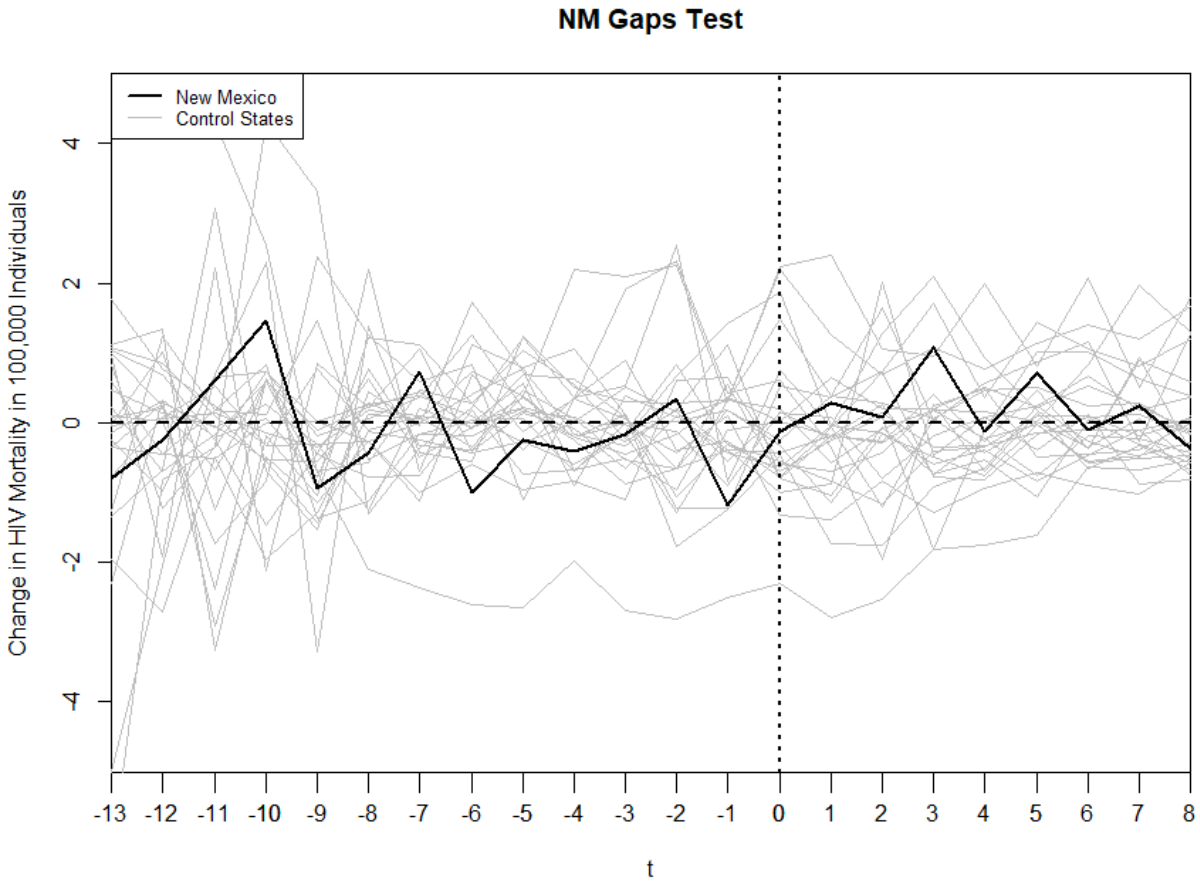


Figure B27: SCM NY healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

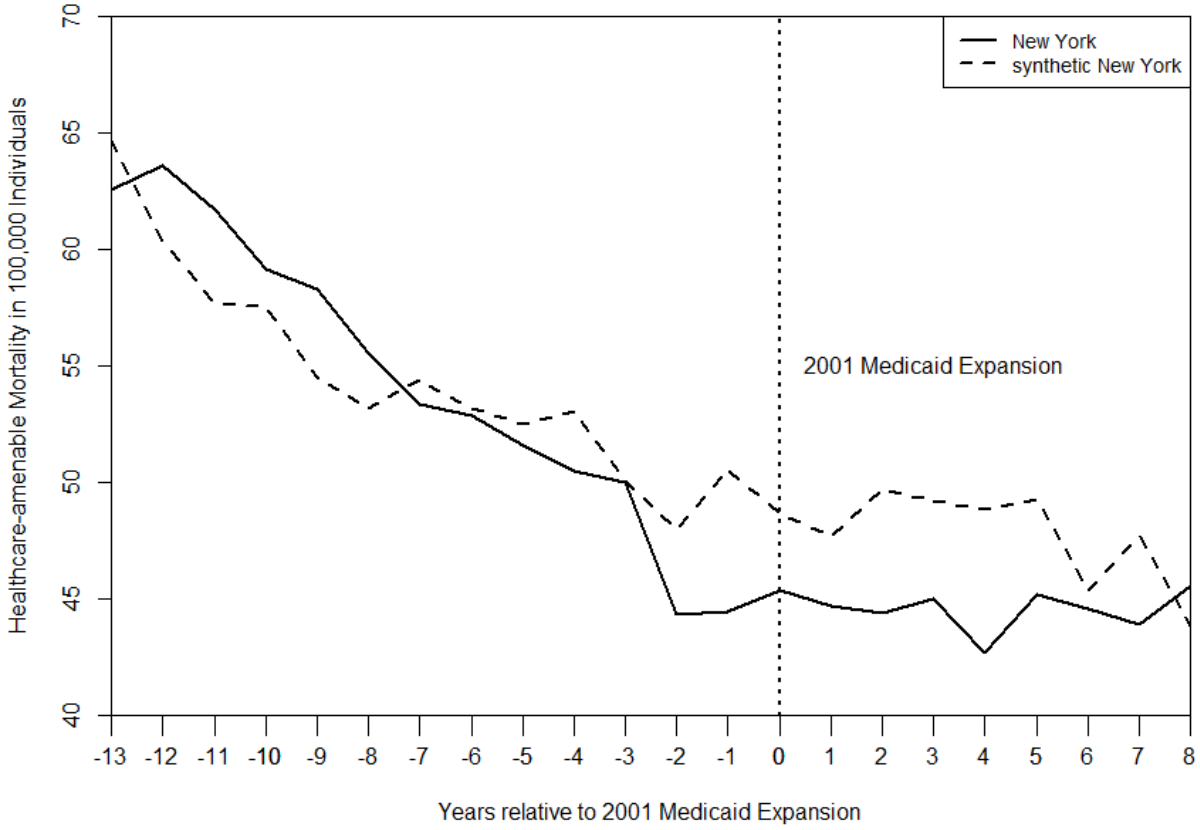


Figure B28: SCM NY healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

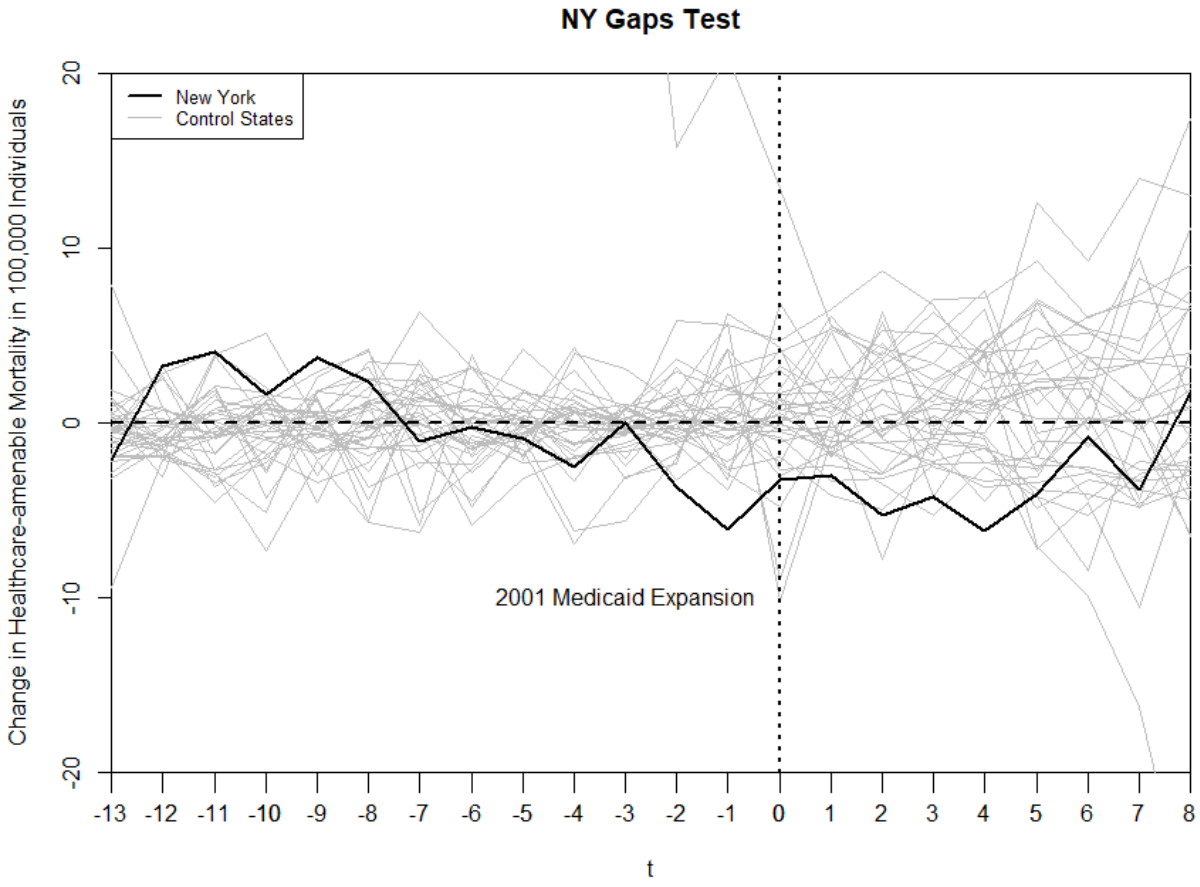


Figure B29: SCM OR healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

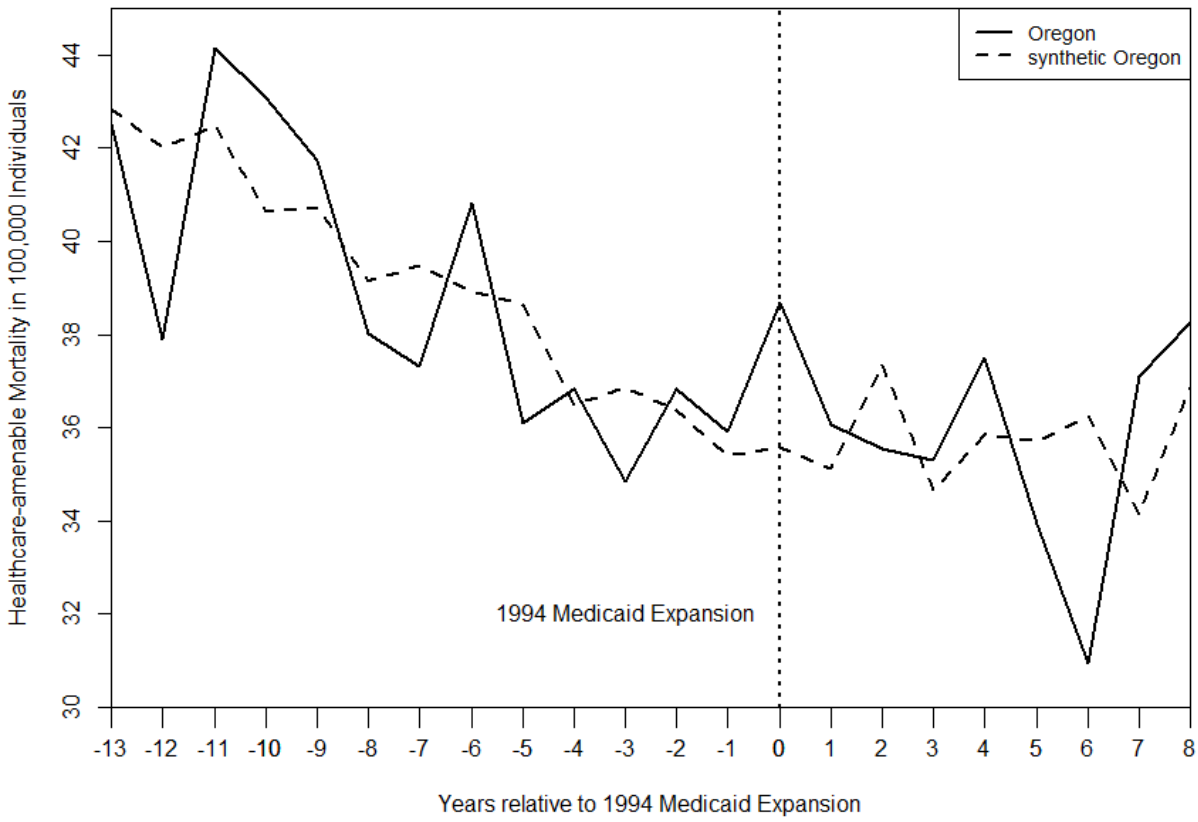


Figure B30: SCM OR healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

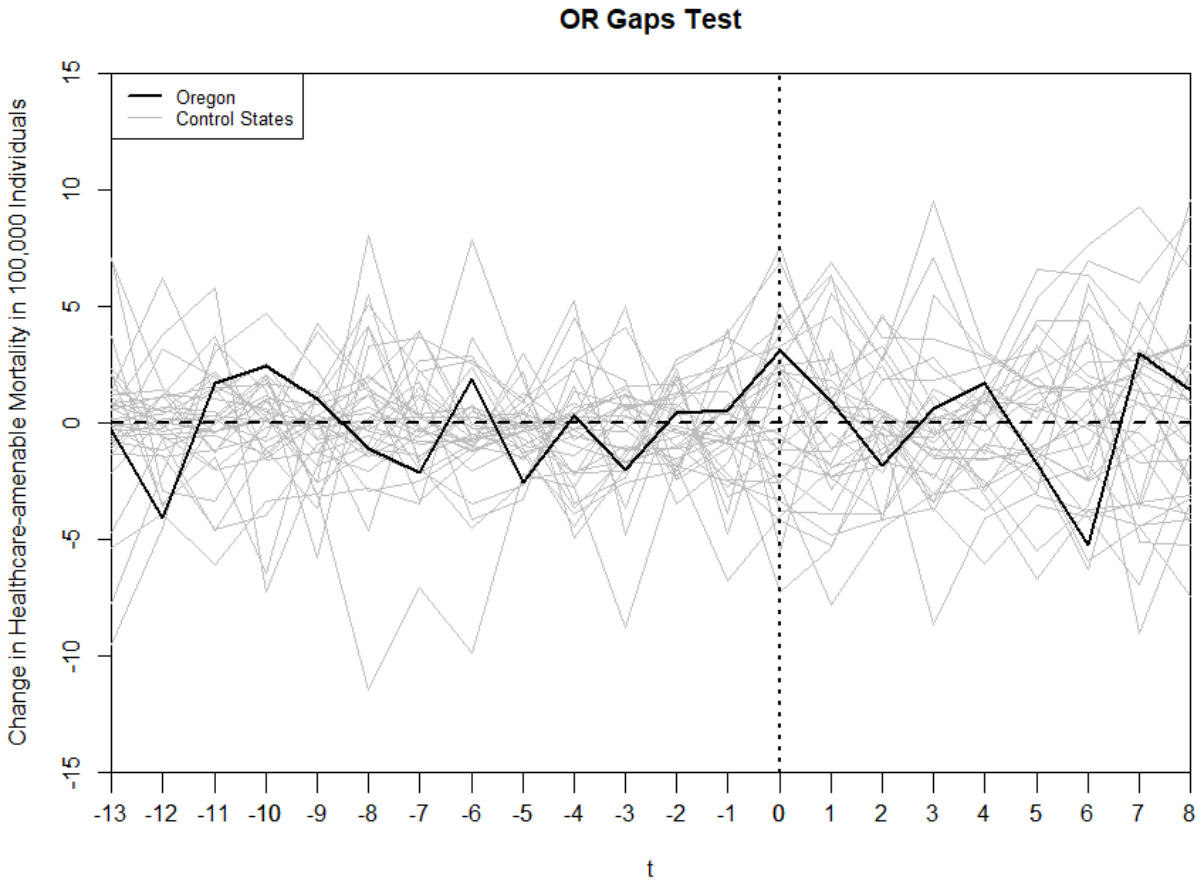


Figure B31: SCM VT healthcare-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

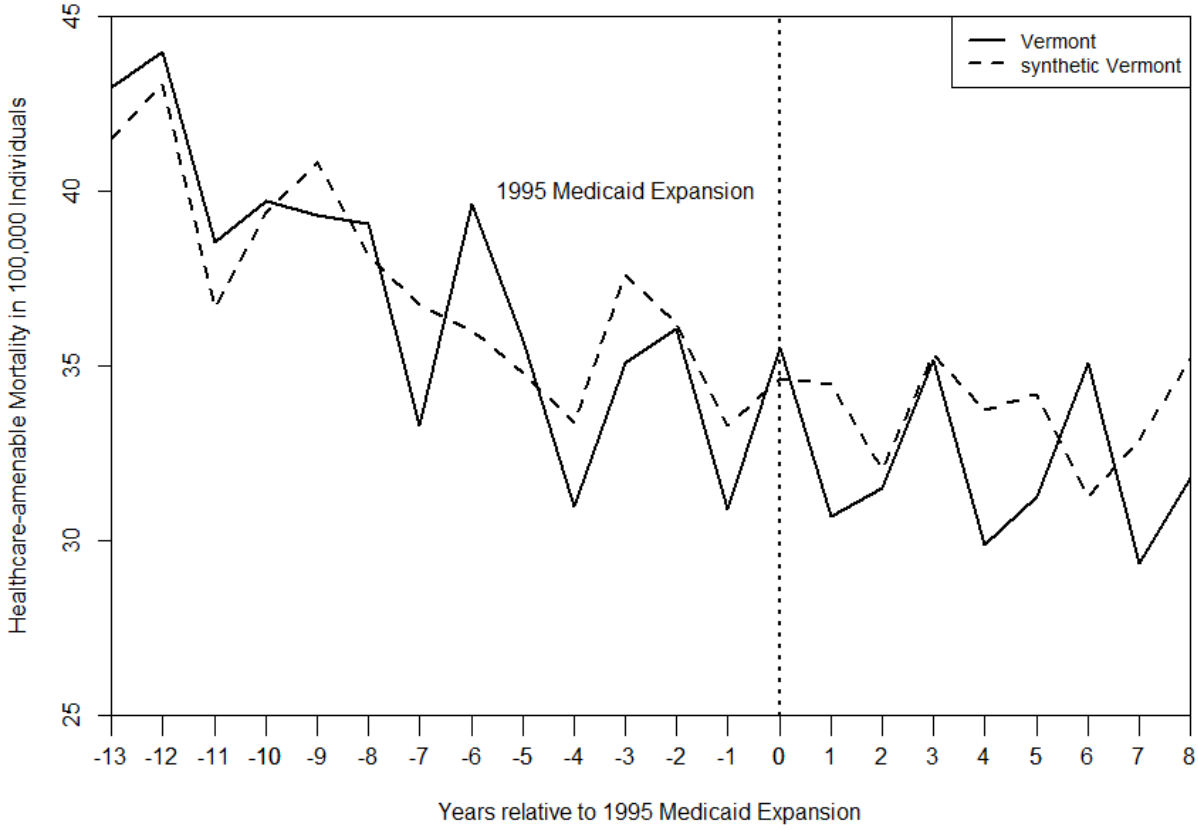


Figure B32: SCM VT healthcare-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

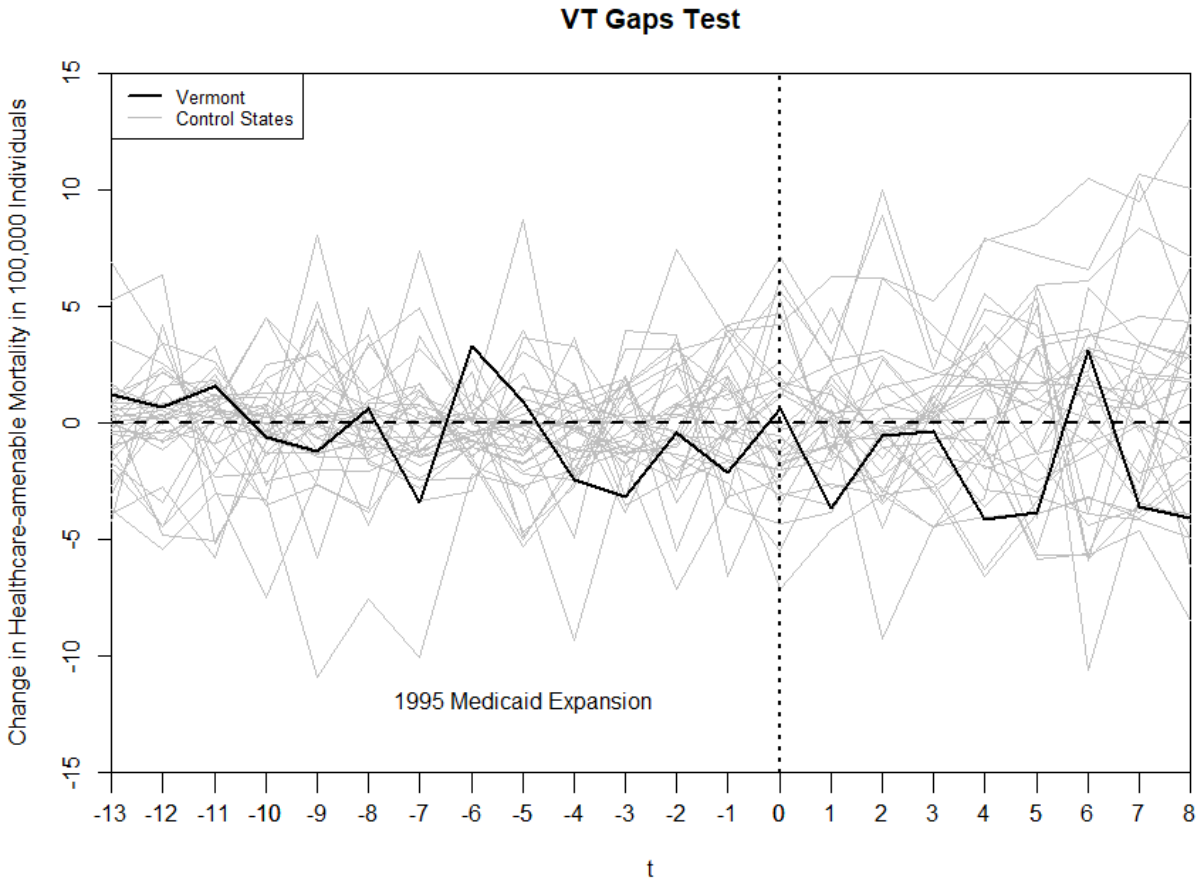


Figure B33: SCM AZ healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

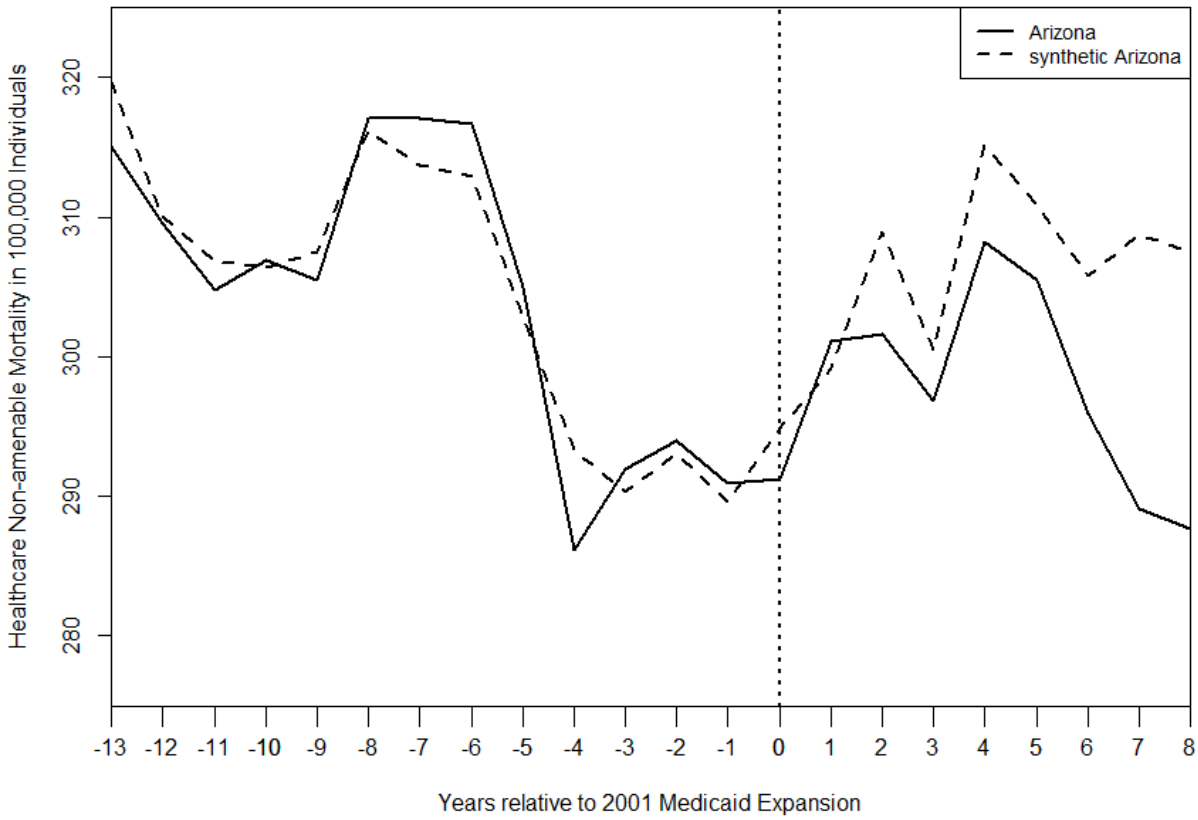


Figure B34: SCM AZ healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

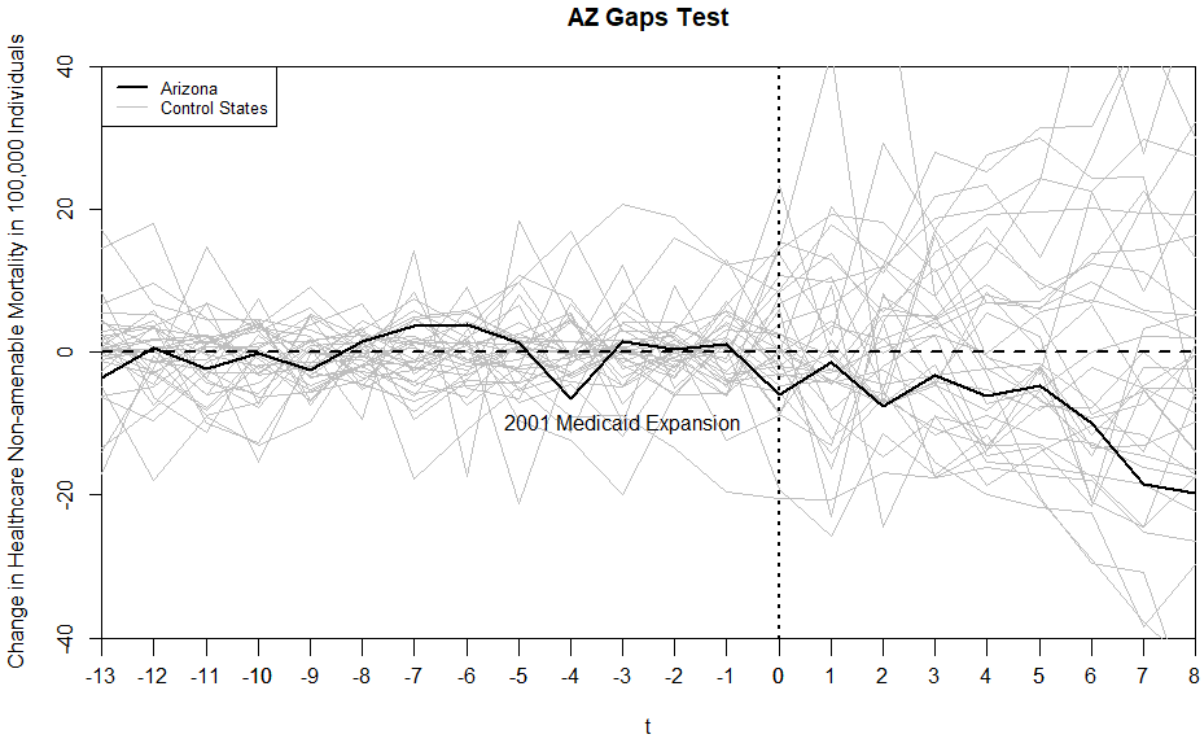


Figure B35: SCM IL healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

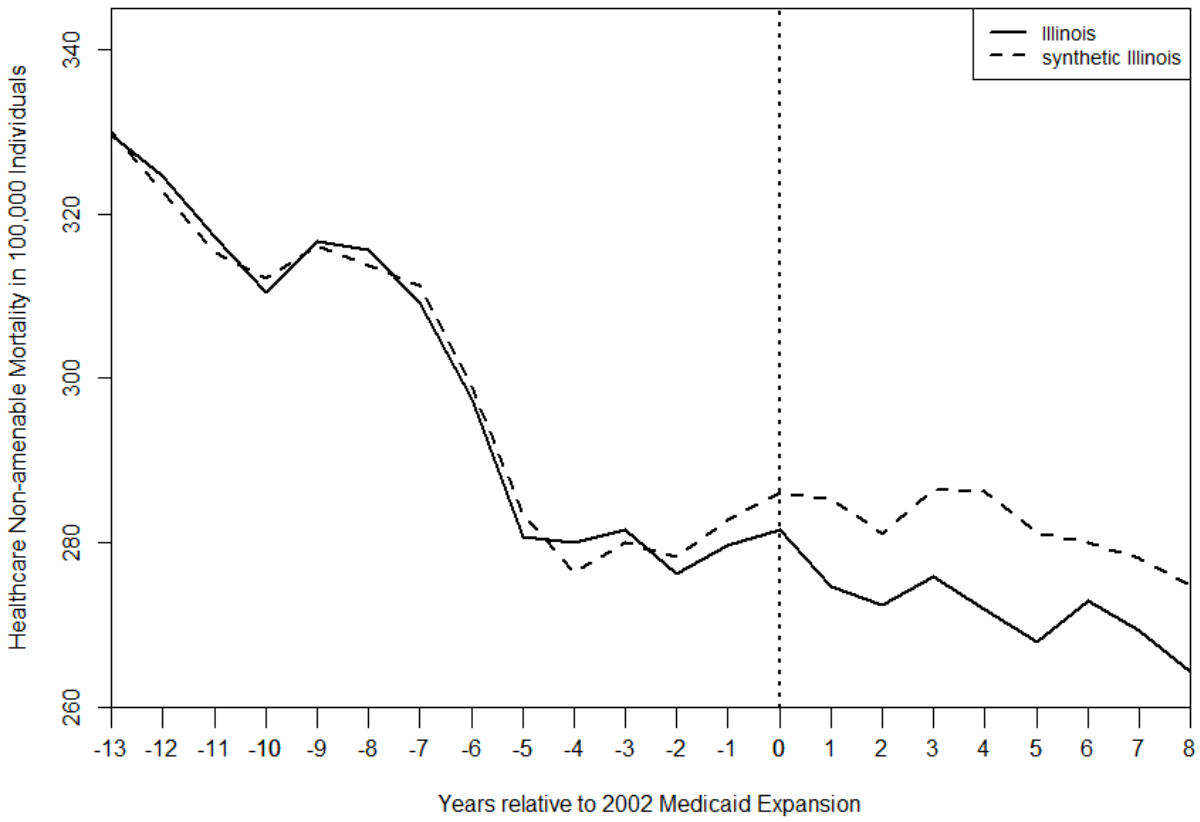


Figure B36: SCM IL healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

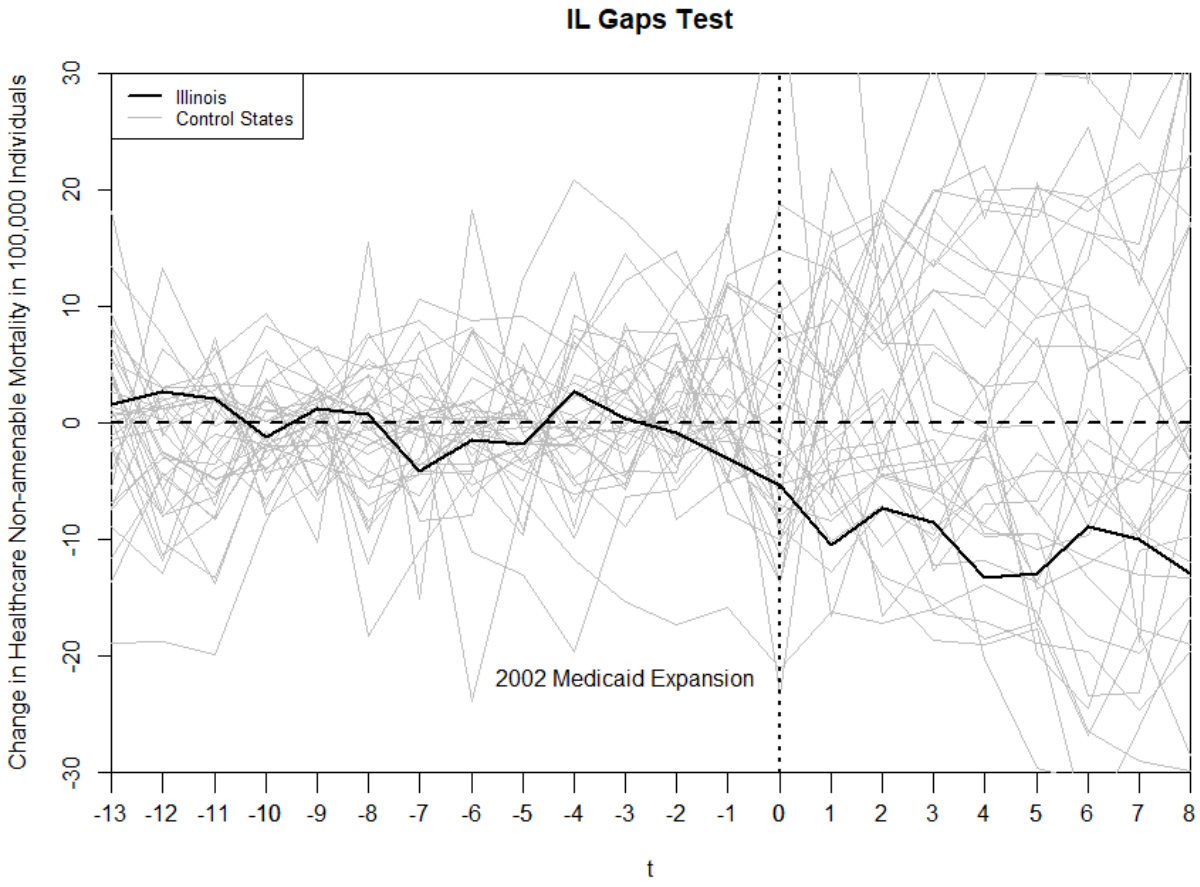


Figure B37: SCM ME healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

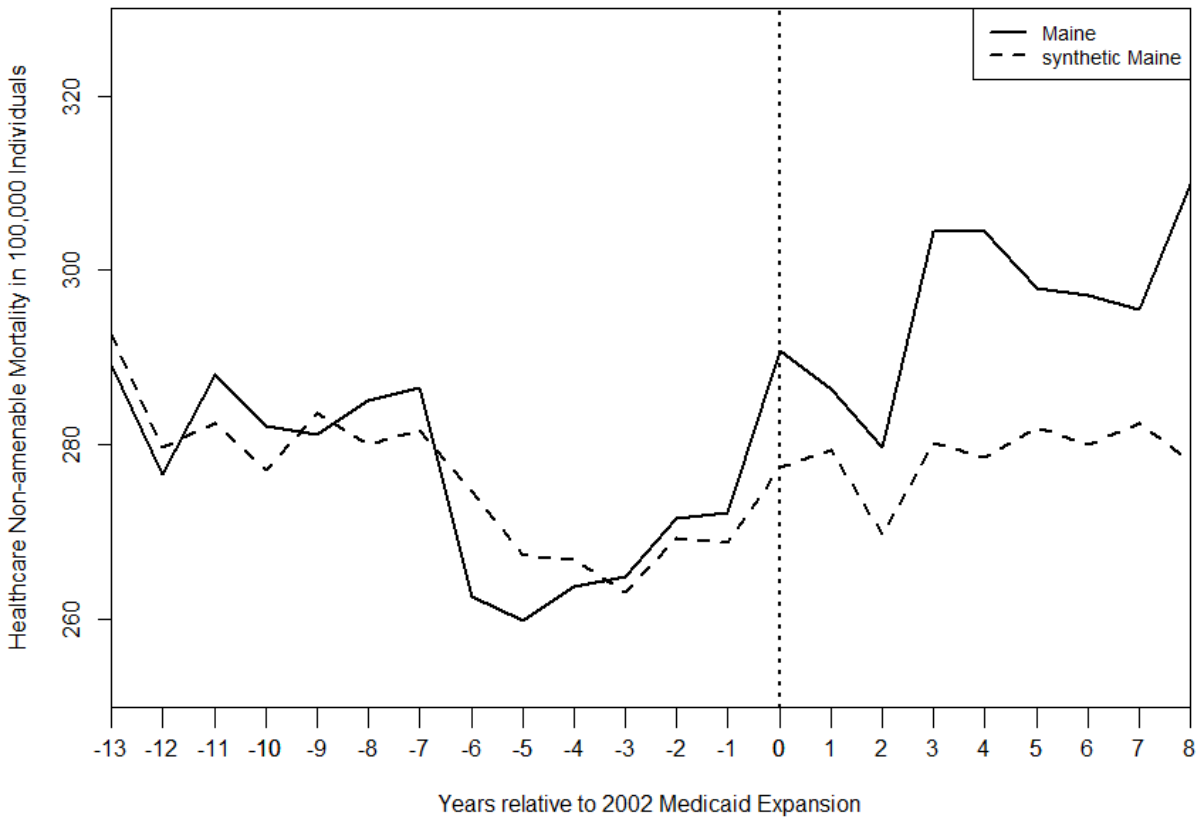


Figure B38: SCM ME healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

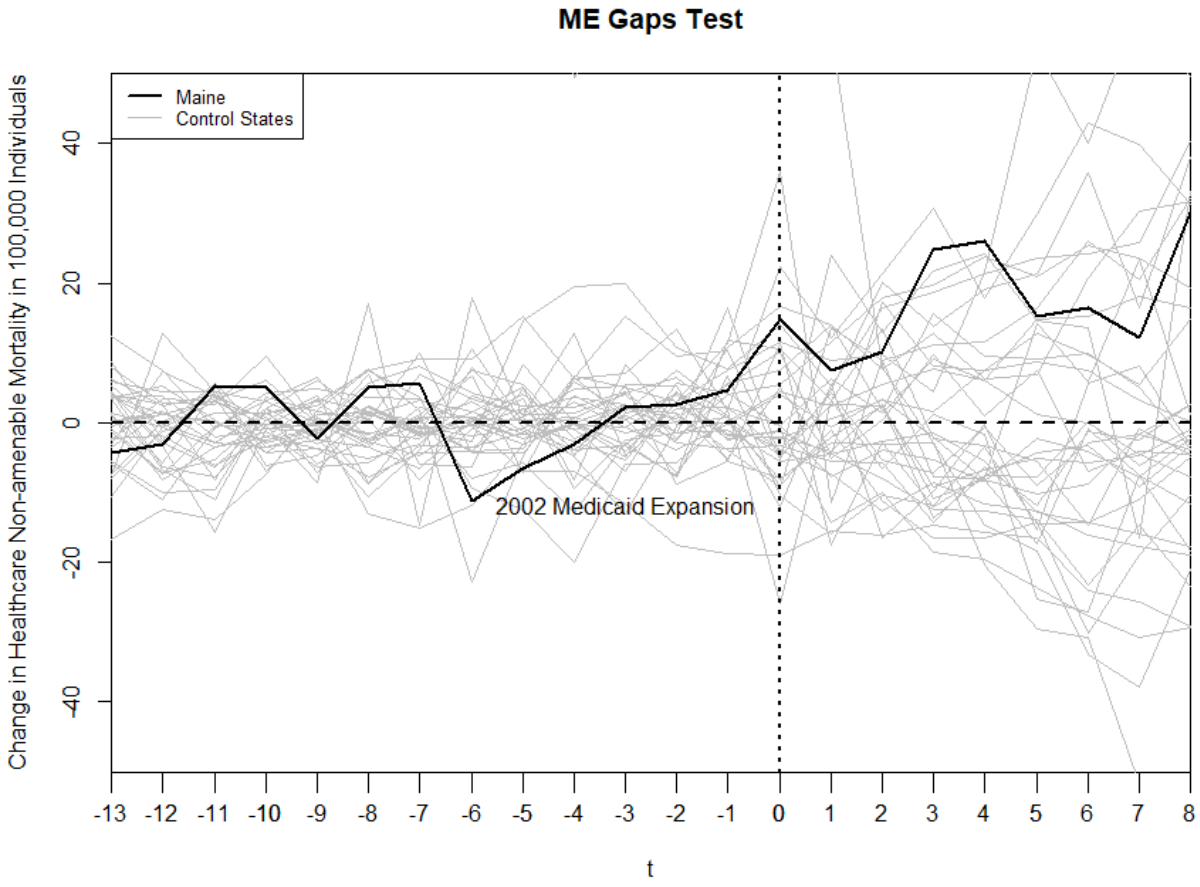


Figure B39: SCM MI healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

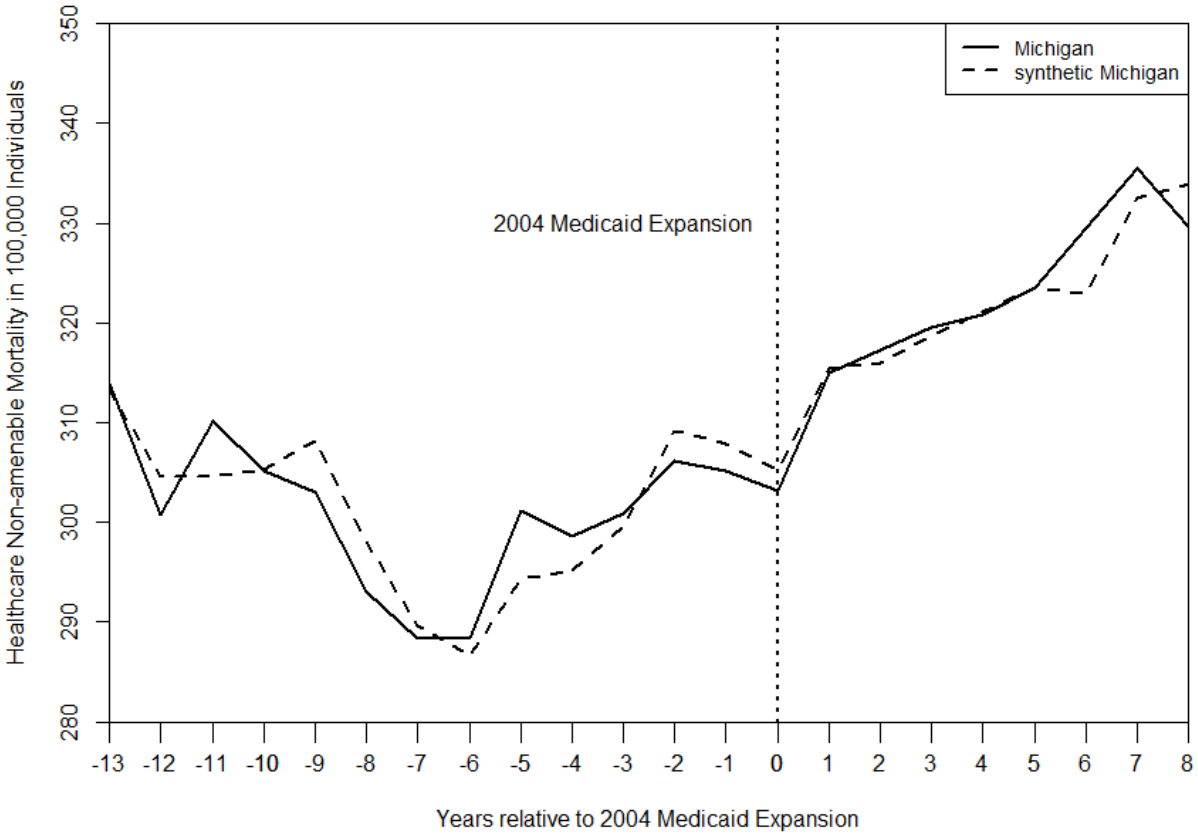


Figure B40: SCM MI healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

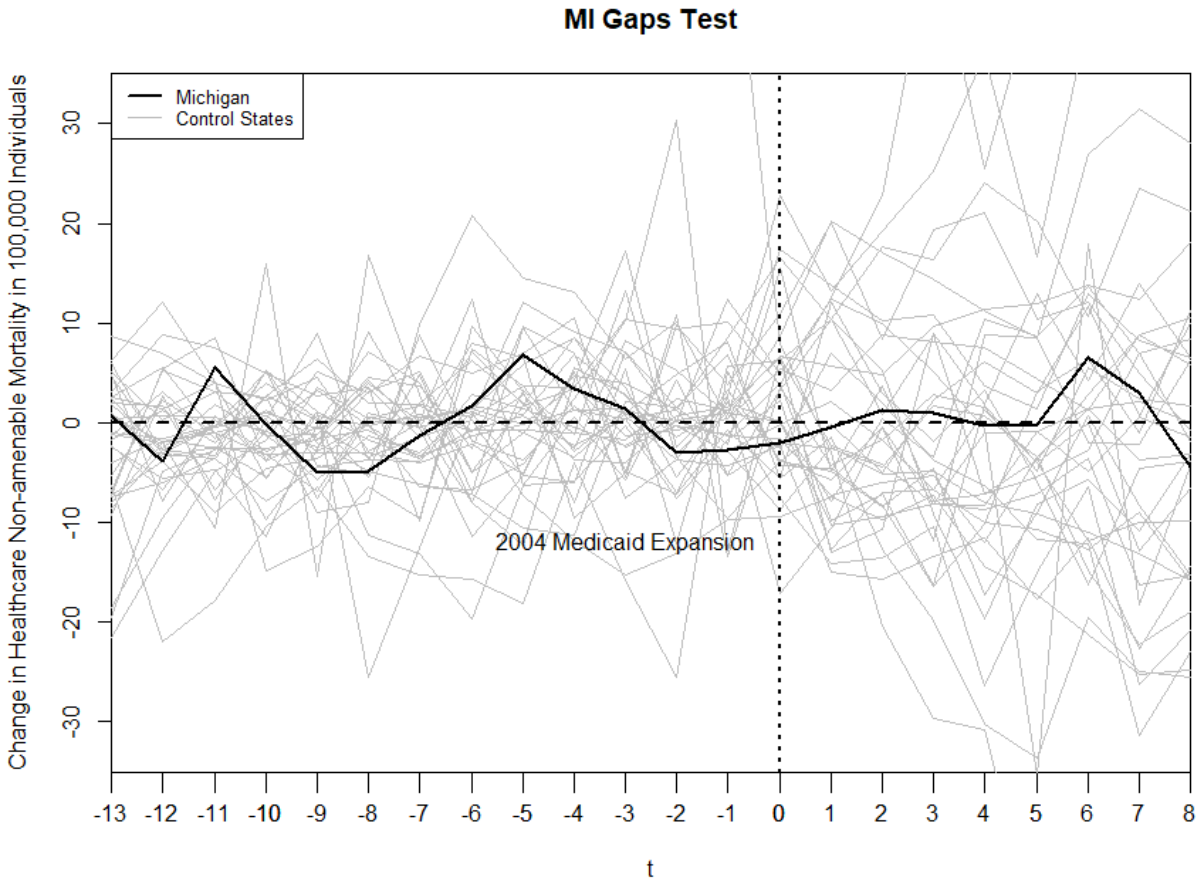


Figure B41: SCM NM healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

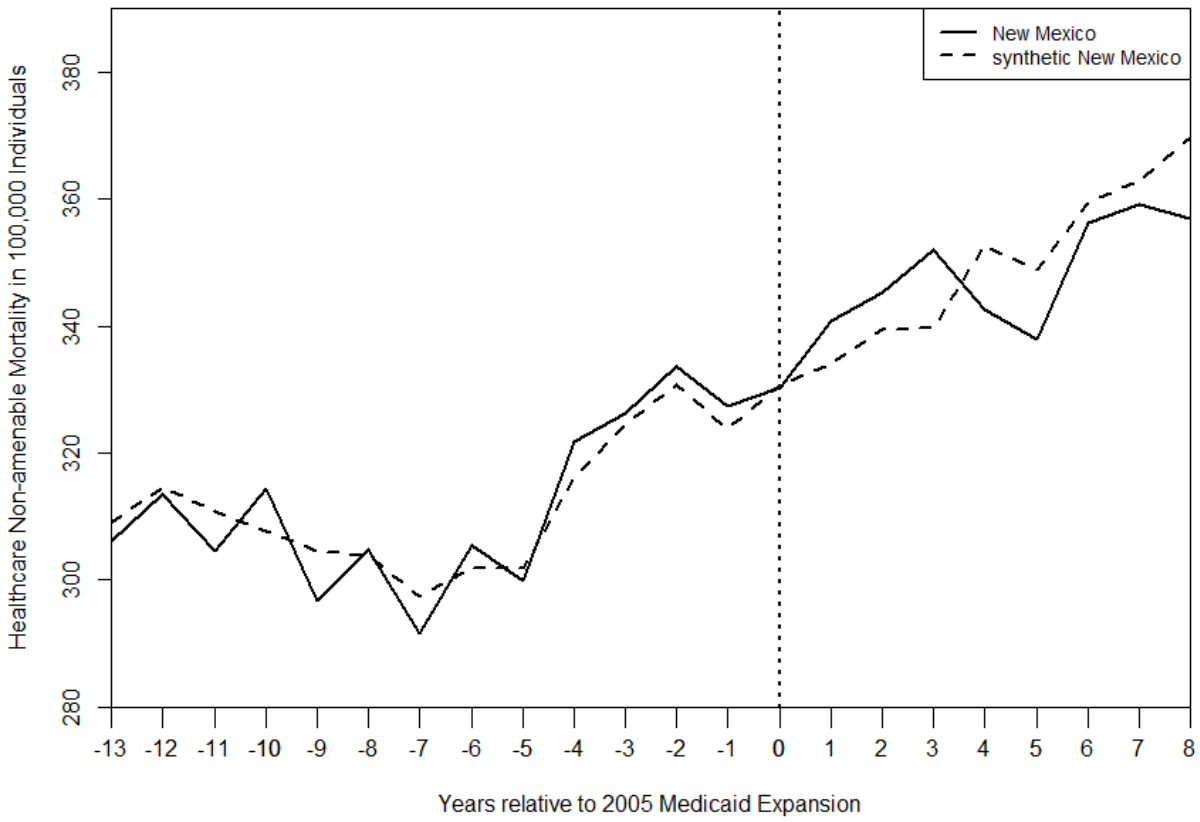


Figure B42: SCM NM healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

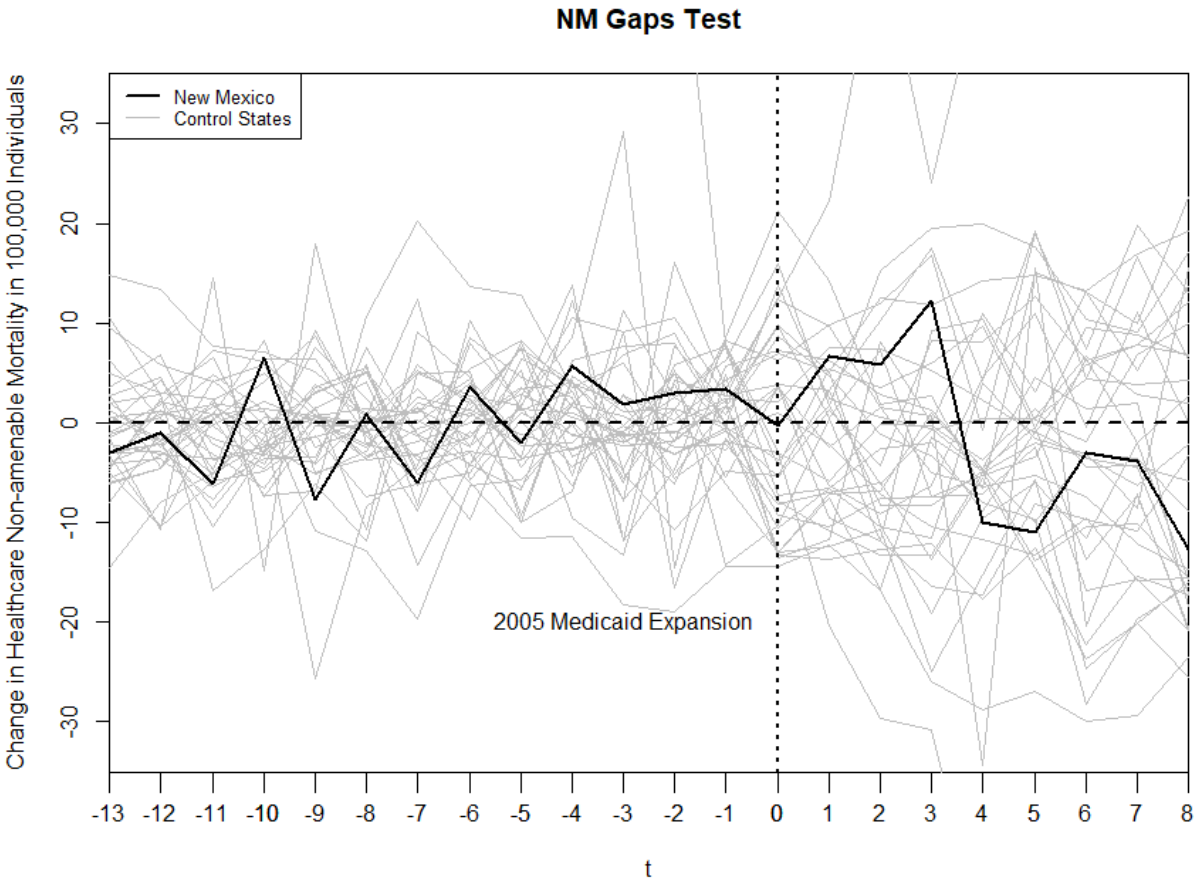


Figure B43: SCM NY healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

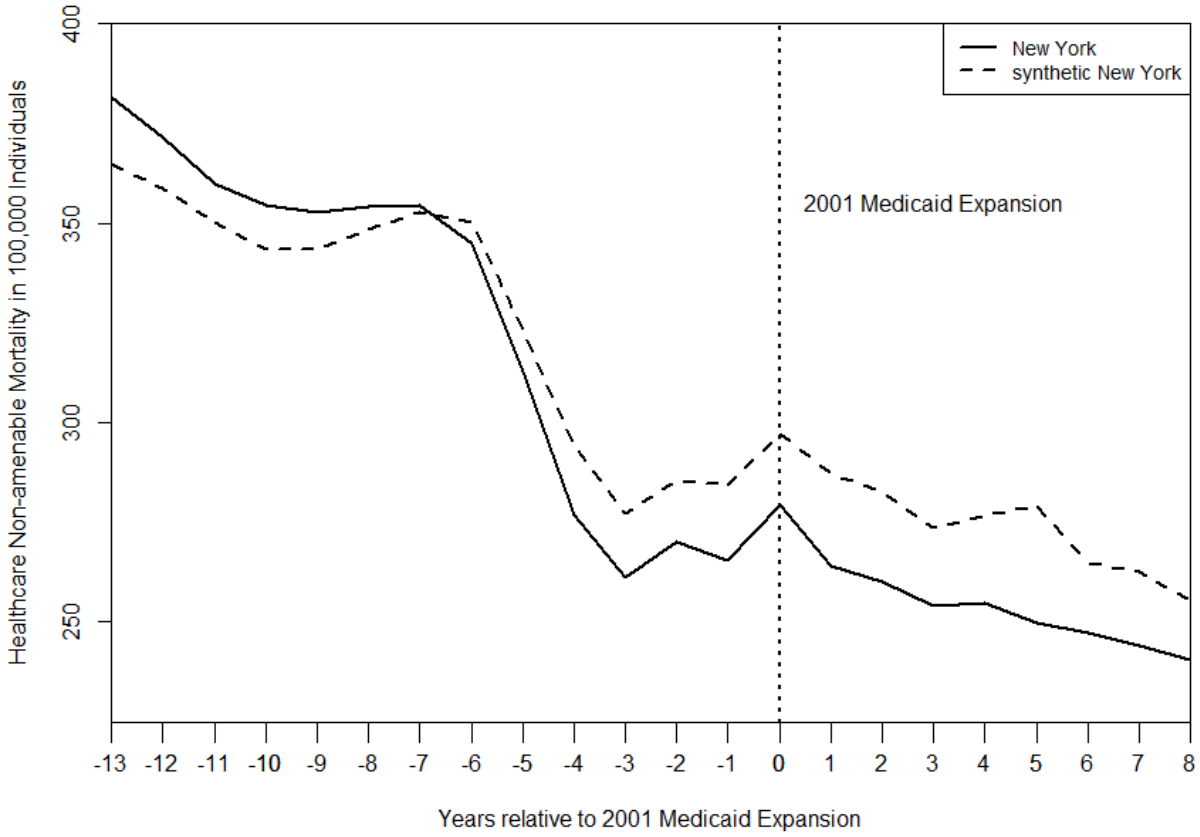


Figure B44: SCM NY healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

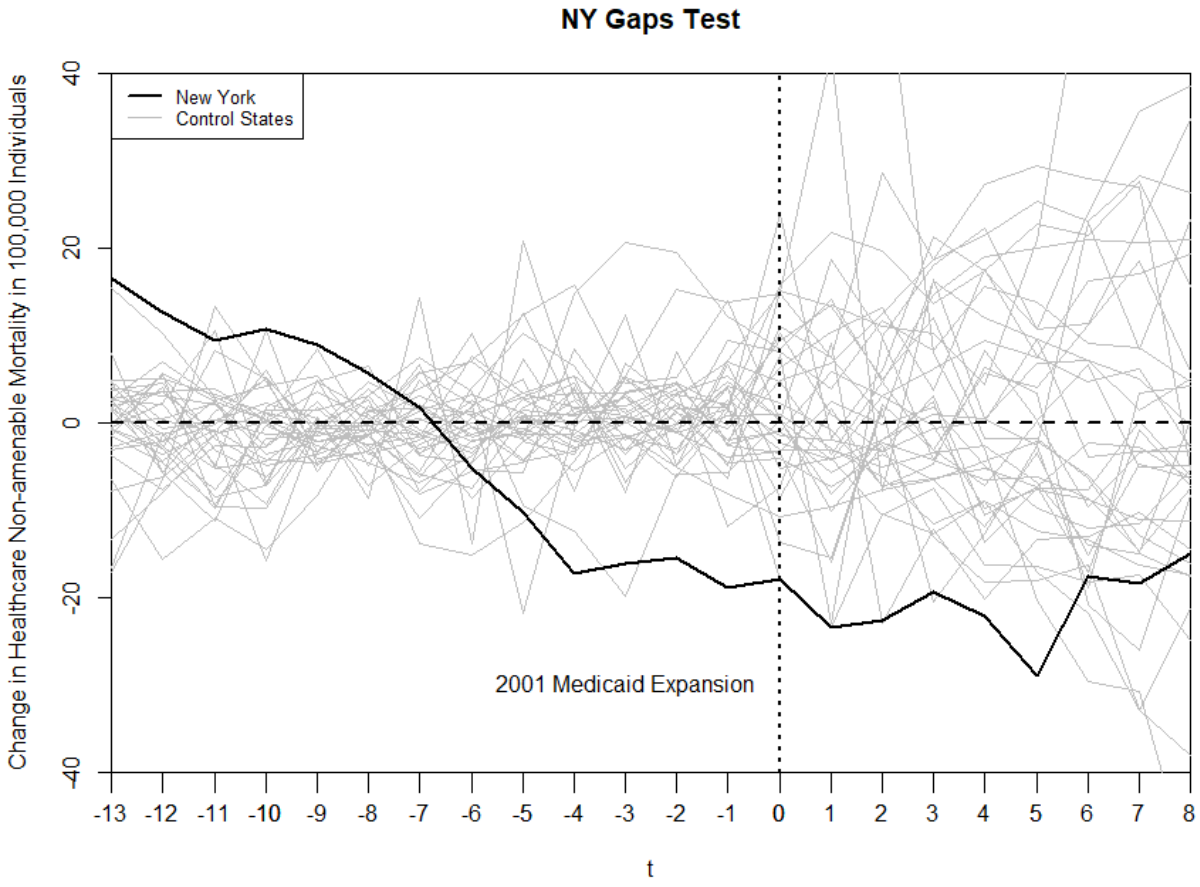


Figure B45: SCM OR healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

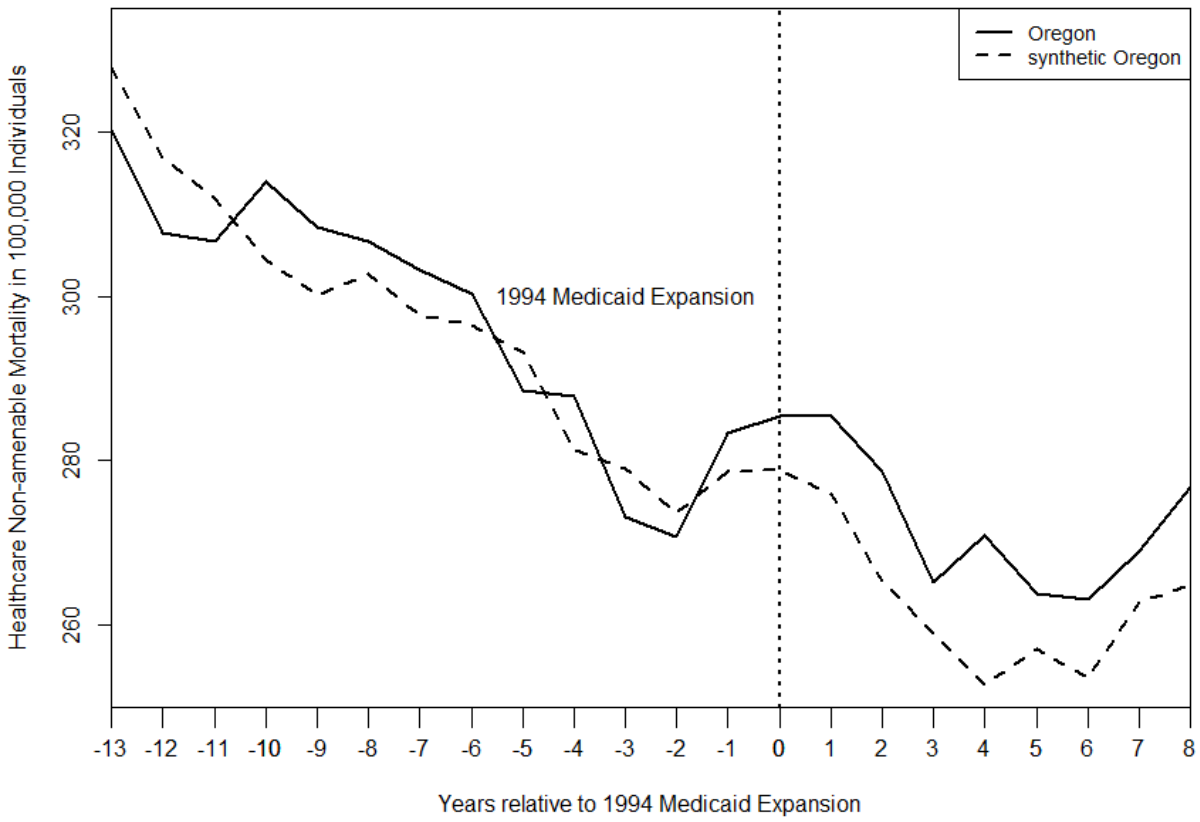


Figure B46: SCM OR healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

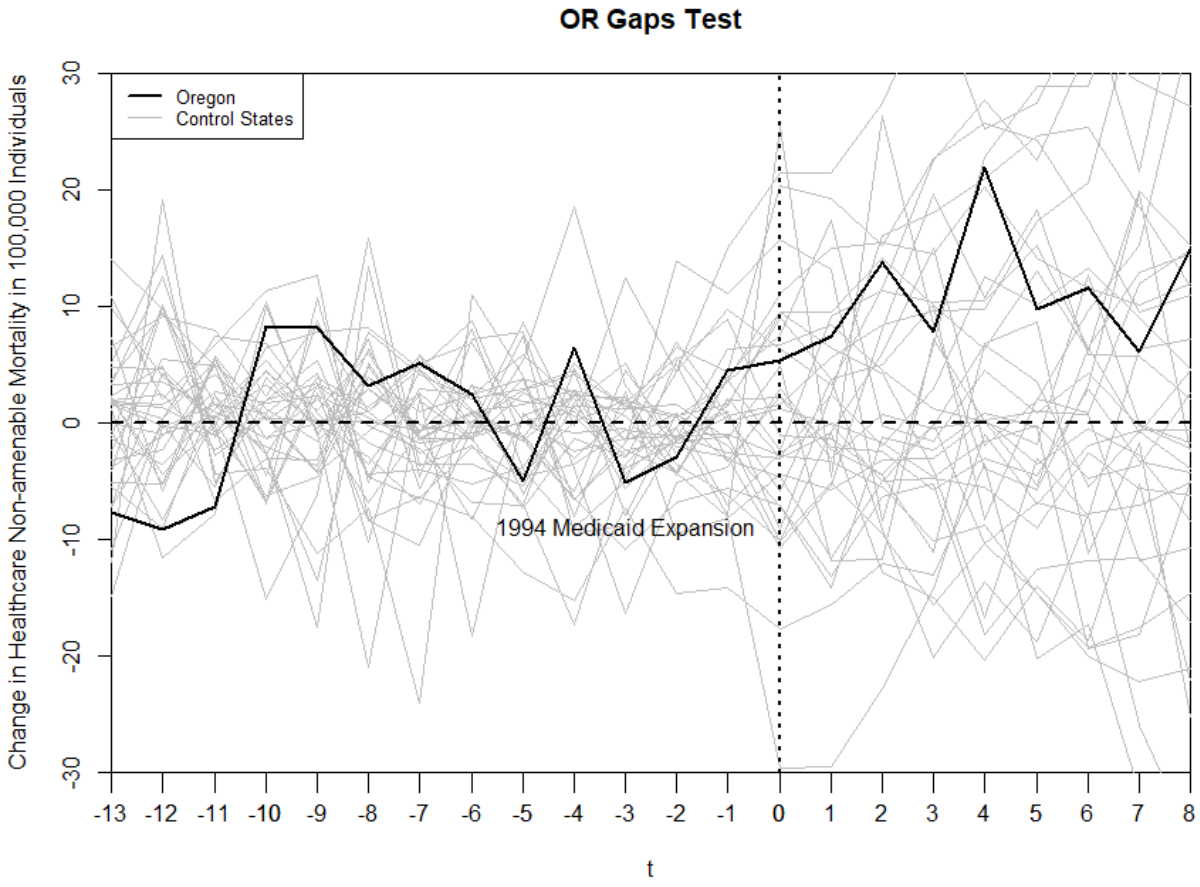


Figure B47: SCM VT healthcare non-amenable mortality rate trends plot, 13 pre- and 8 post-treatment years

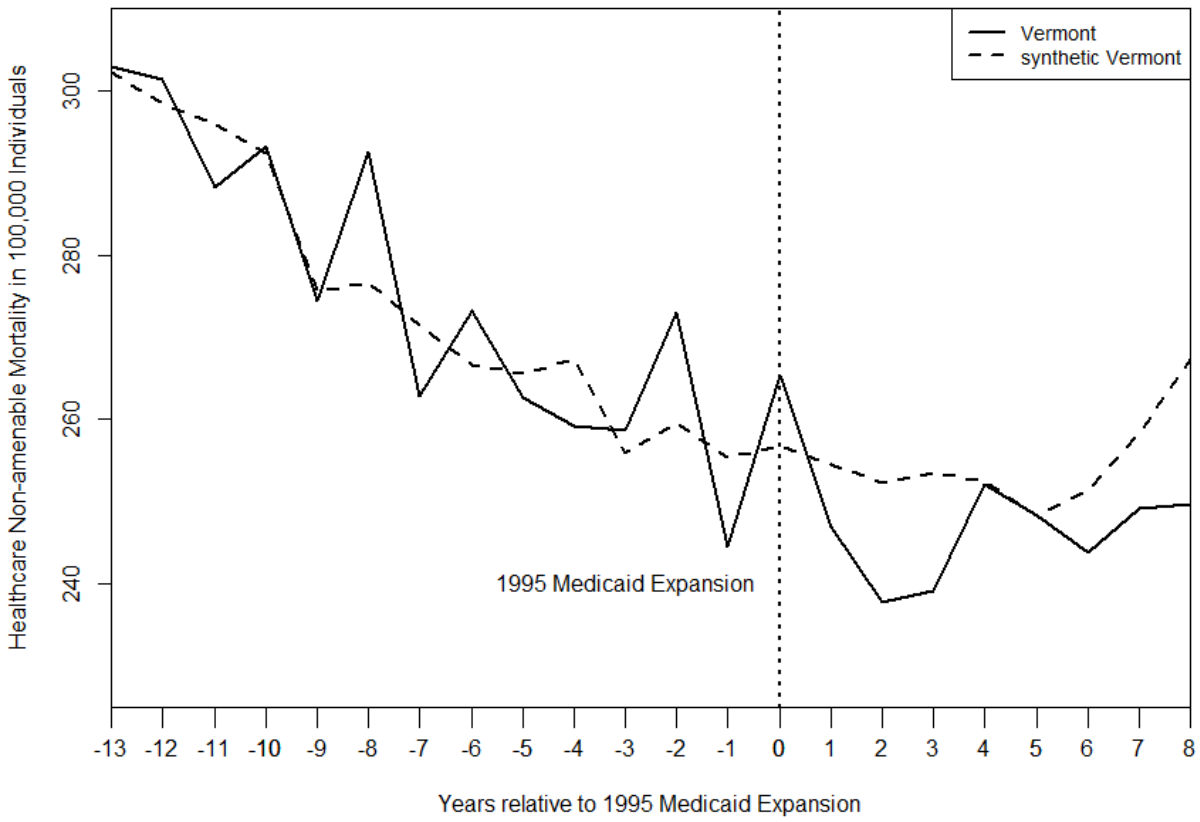


Figure B48: SCM VT healthcare non-amenable mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

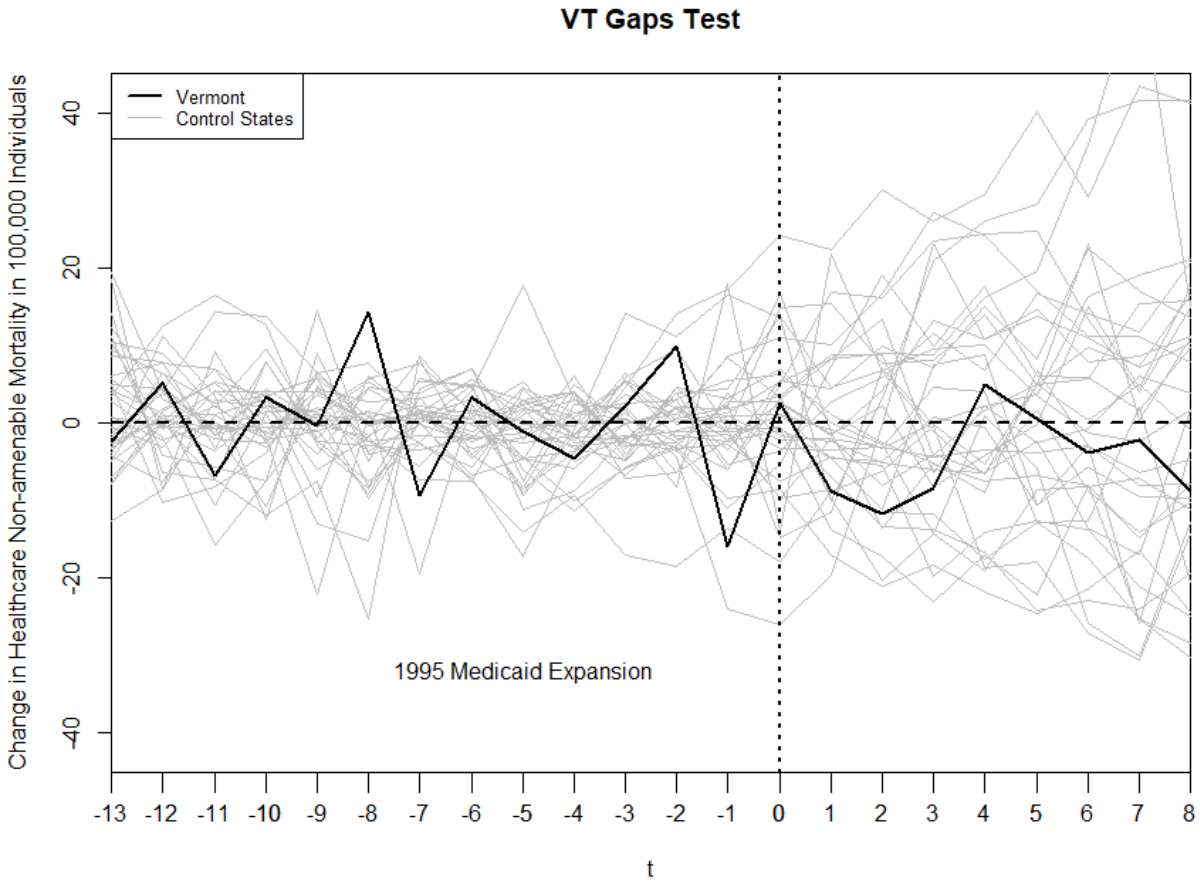


Figure B49: SCM AZ HIV mortality rate trends plot, 13 pre- and 8 post-treatment years

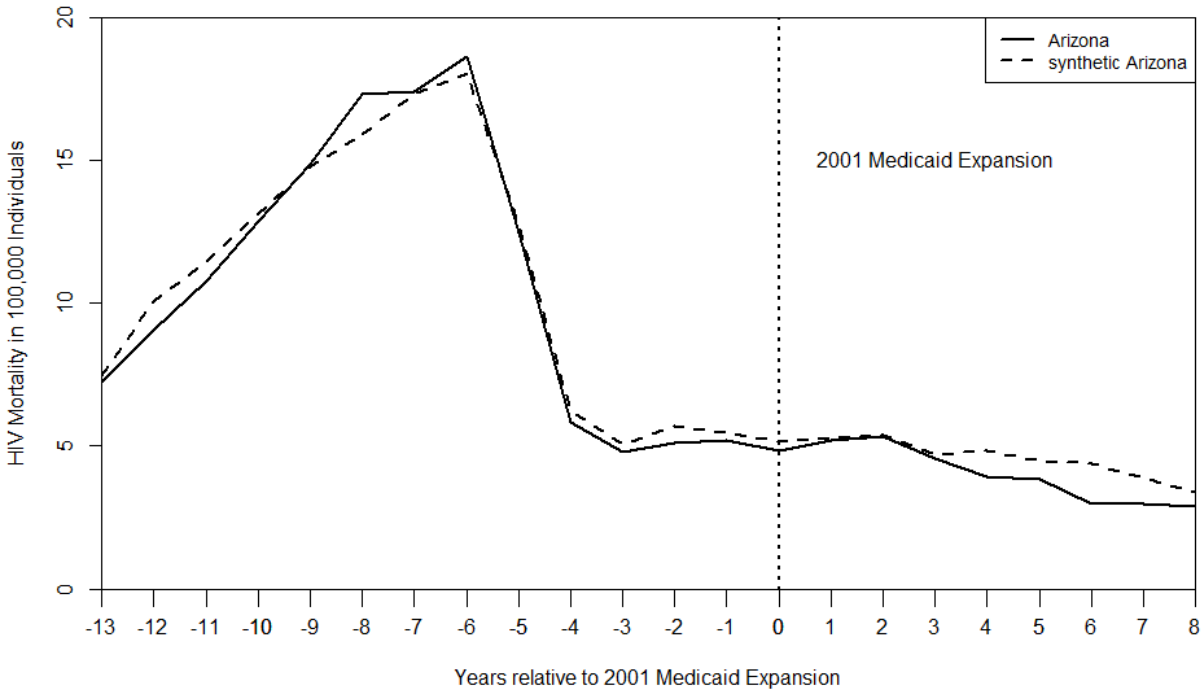


Figure B50: SCM AZ HIV mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

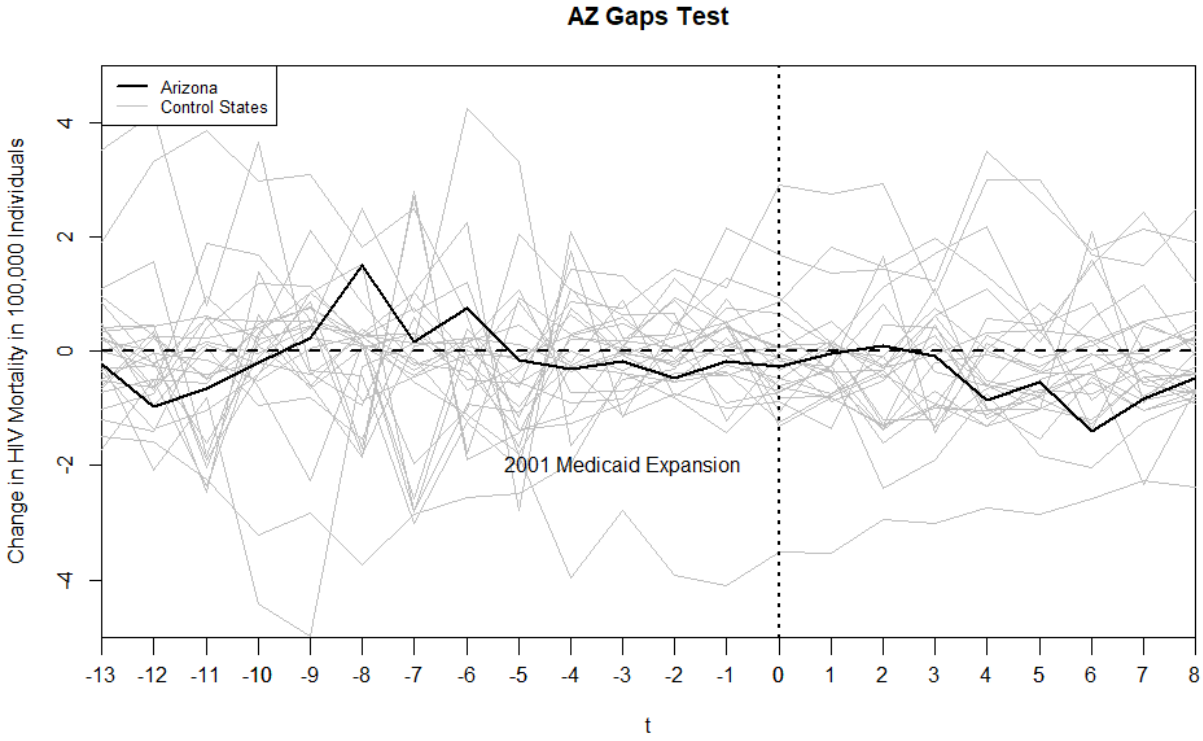


Figure B51: SCM IL HIV mortality rate trends plot, 13 pre- and 8 post-treatment years

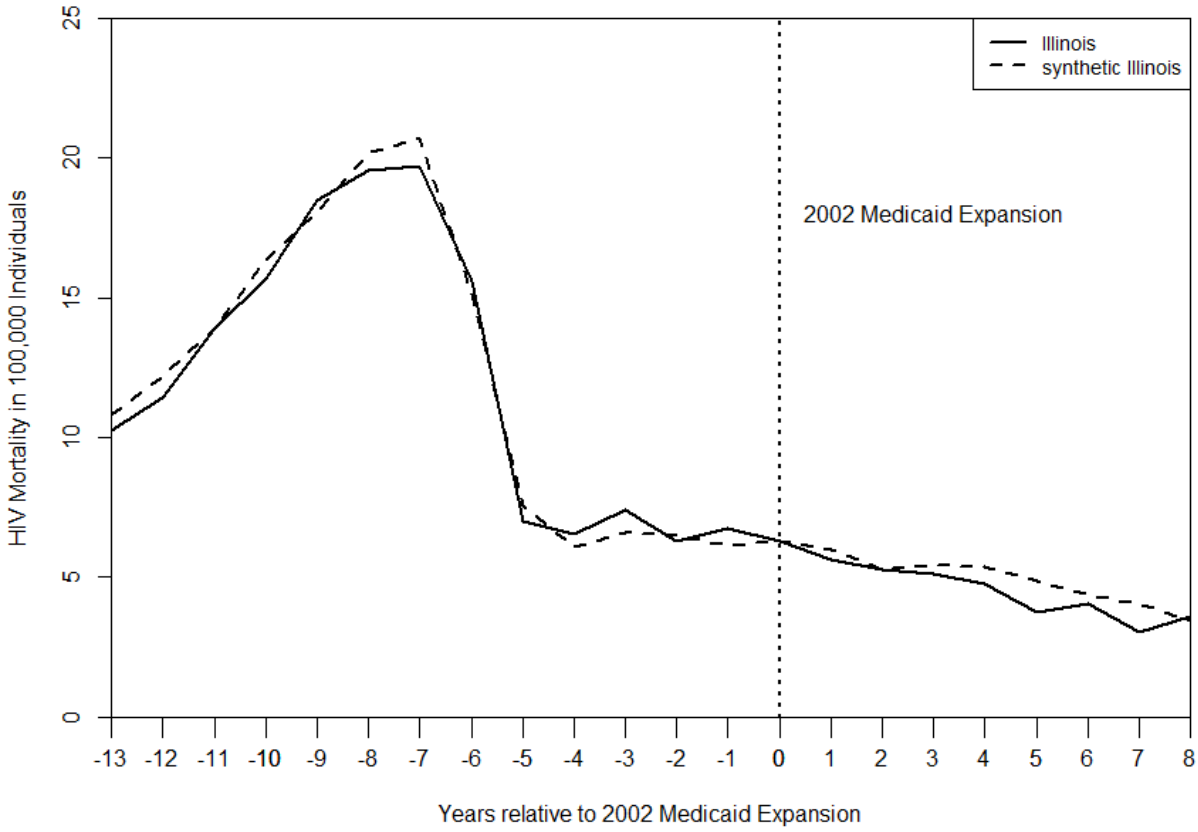


Figure B52: SCM IL HIV mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

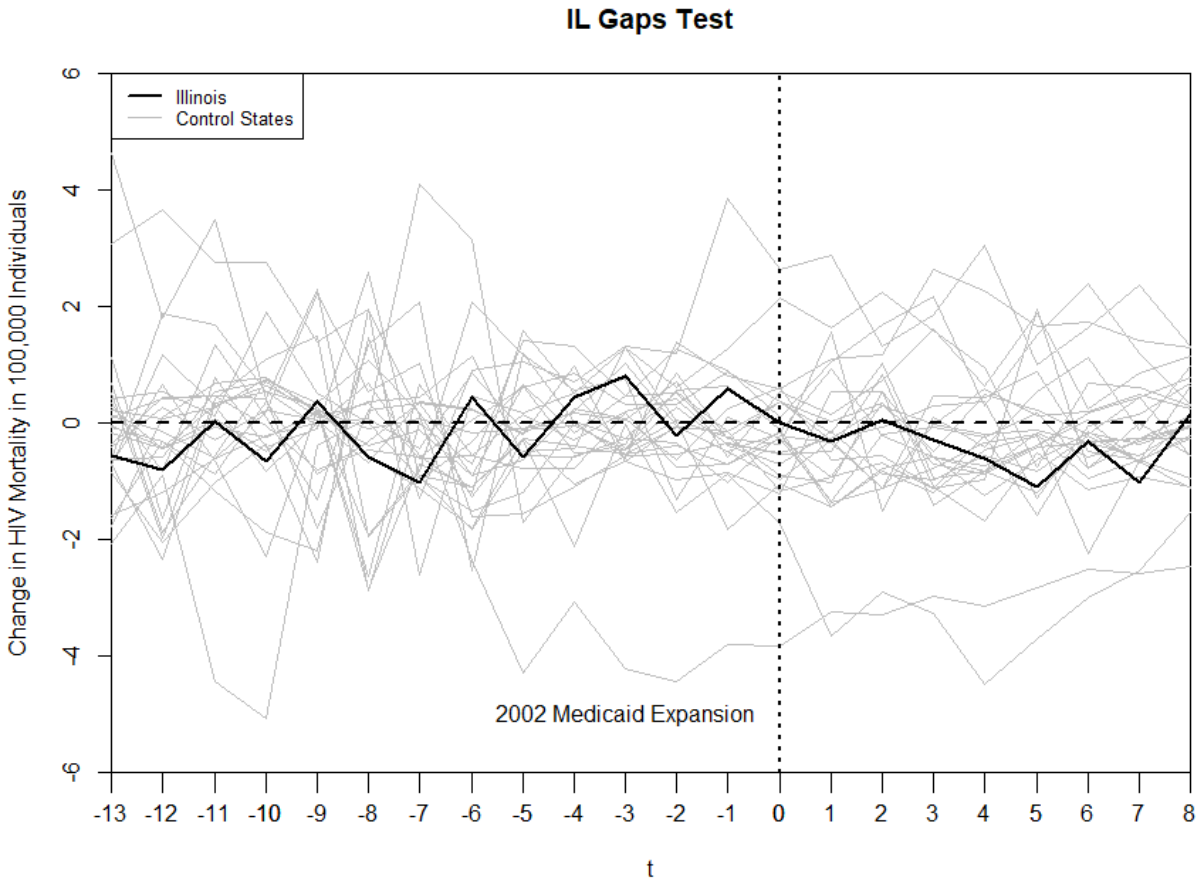


Figure B53: SCM MI HIV mortality rate trends plot, 13 pre- and 8 post-treatment years

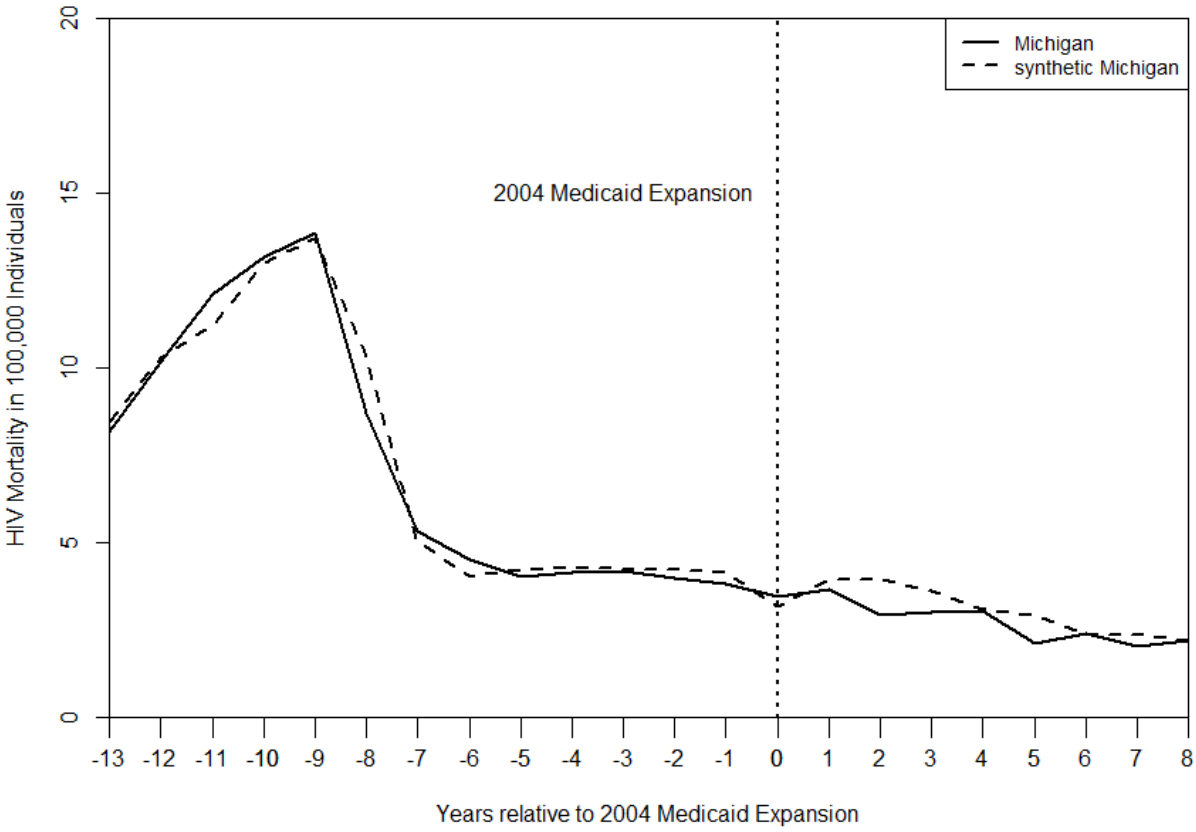


Figure B54: SCM MI HIV mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

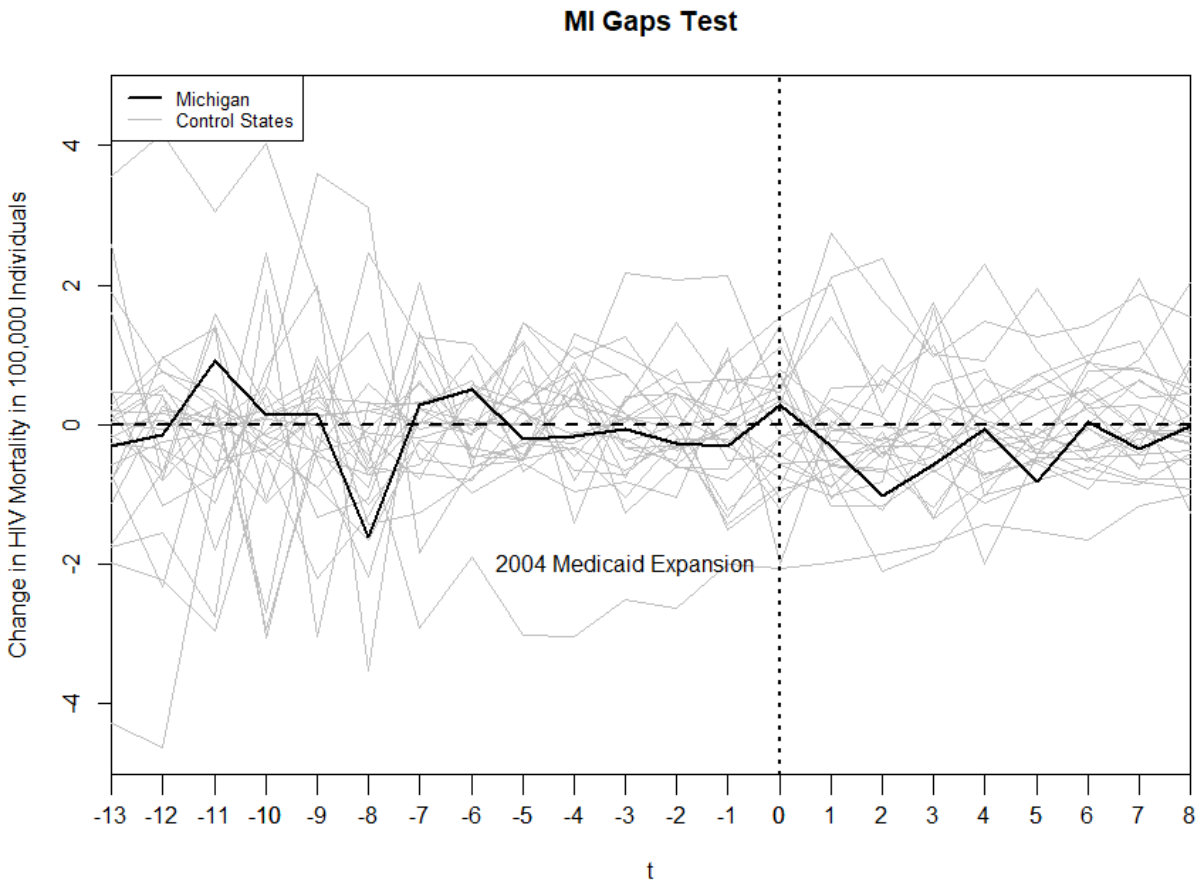


Figure B55: SCM NM HIV mortality rate trends plot, 13 pre- and 8 post-treatment years

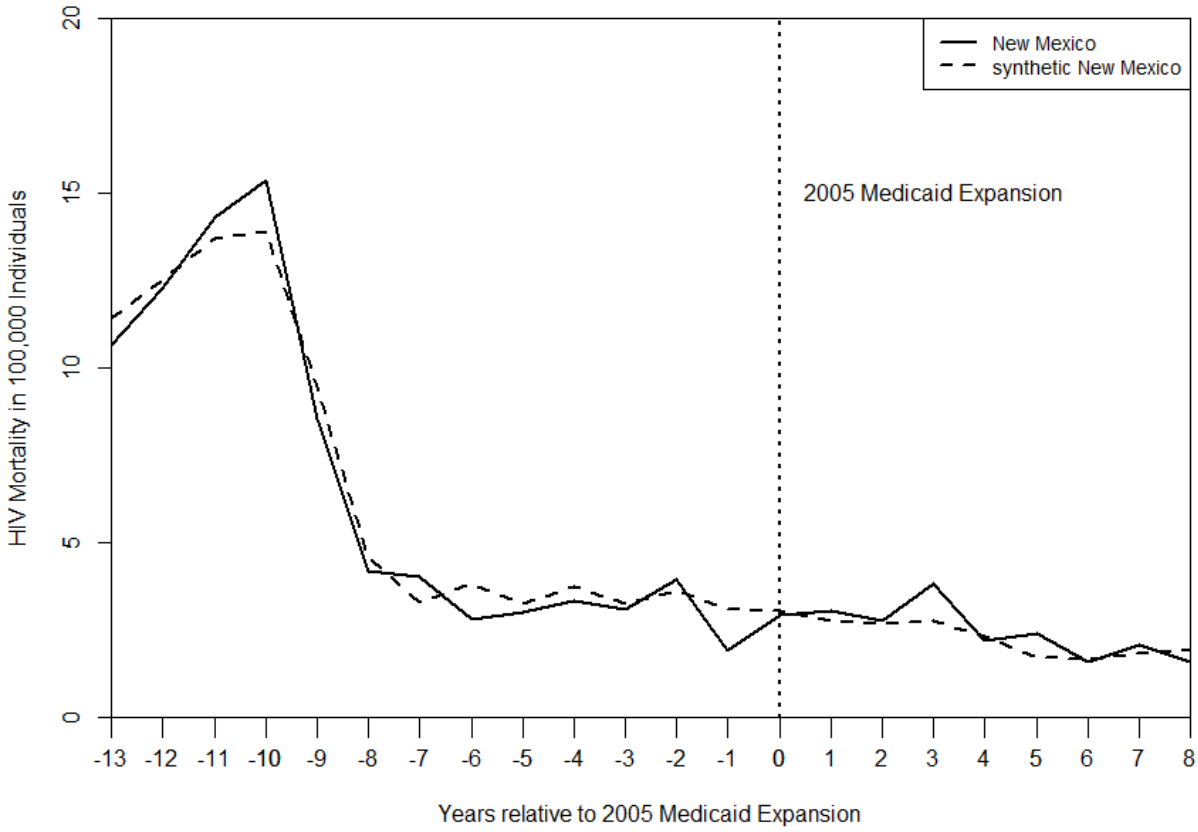


Figure B56: SCM NM HIV mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

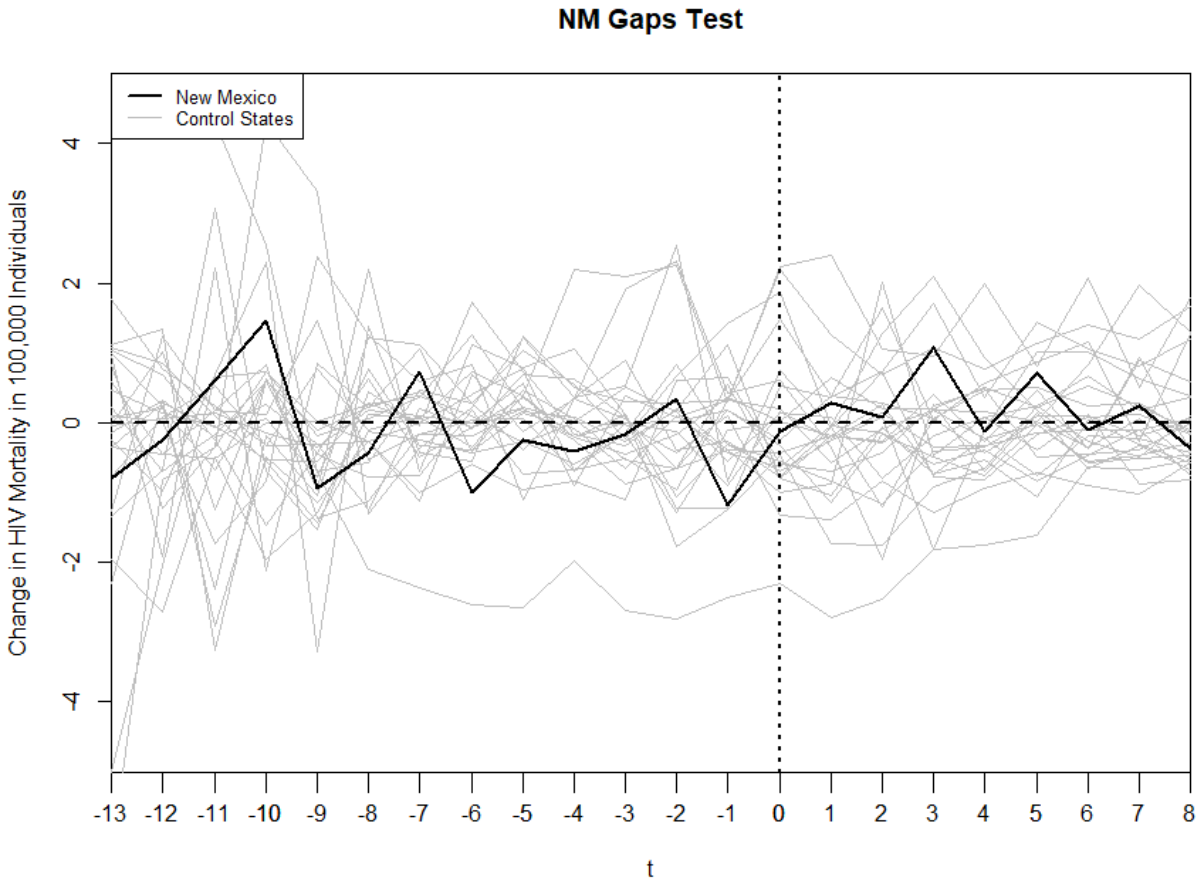


Figure B57: SCM NY HIV mortality rate trends plot, 13 pre- and 8 post-treatment years

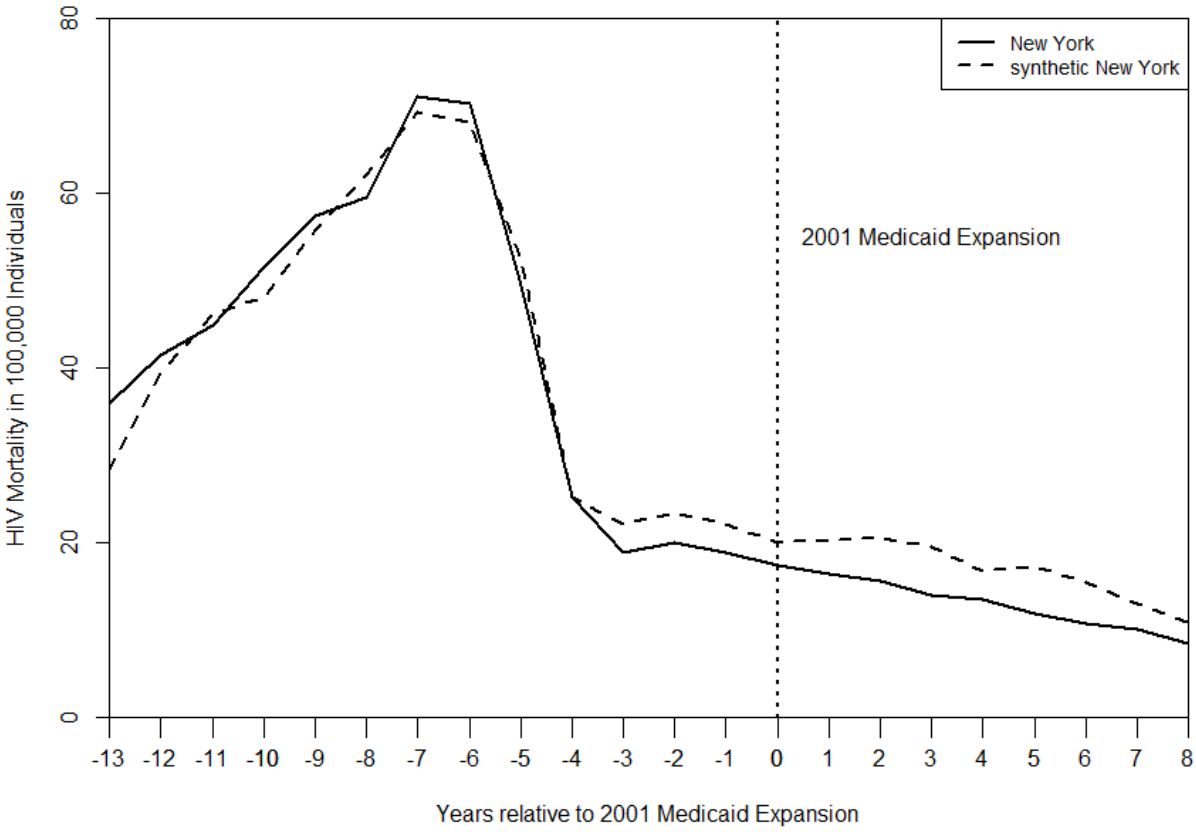


Figure B58: SCM NY HIV mortality rate counterfactual plot, 13 pre- and 8 post-treatment years

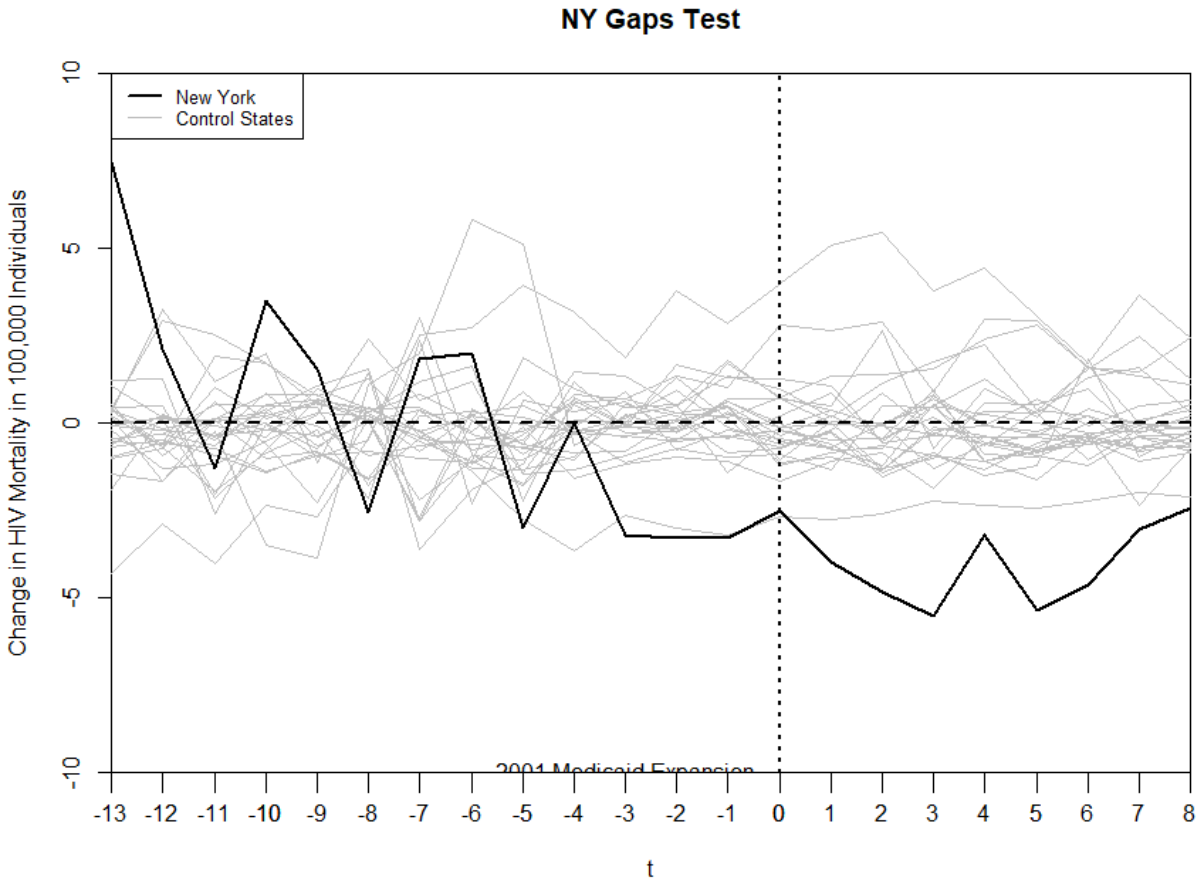


Figure B59: SCM OR HIV mortality rate trends plot, 13 pre- and 8 post-treatment years

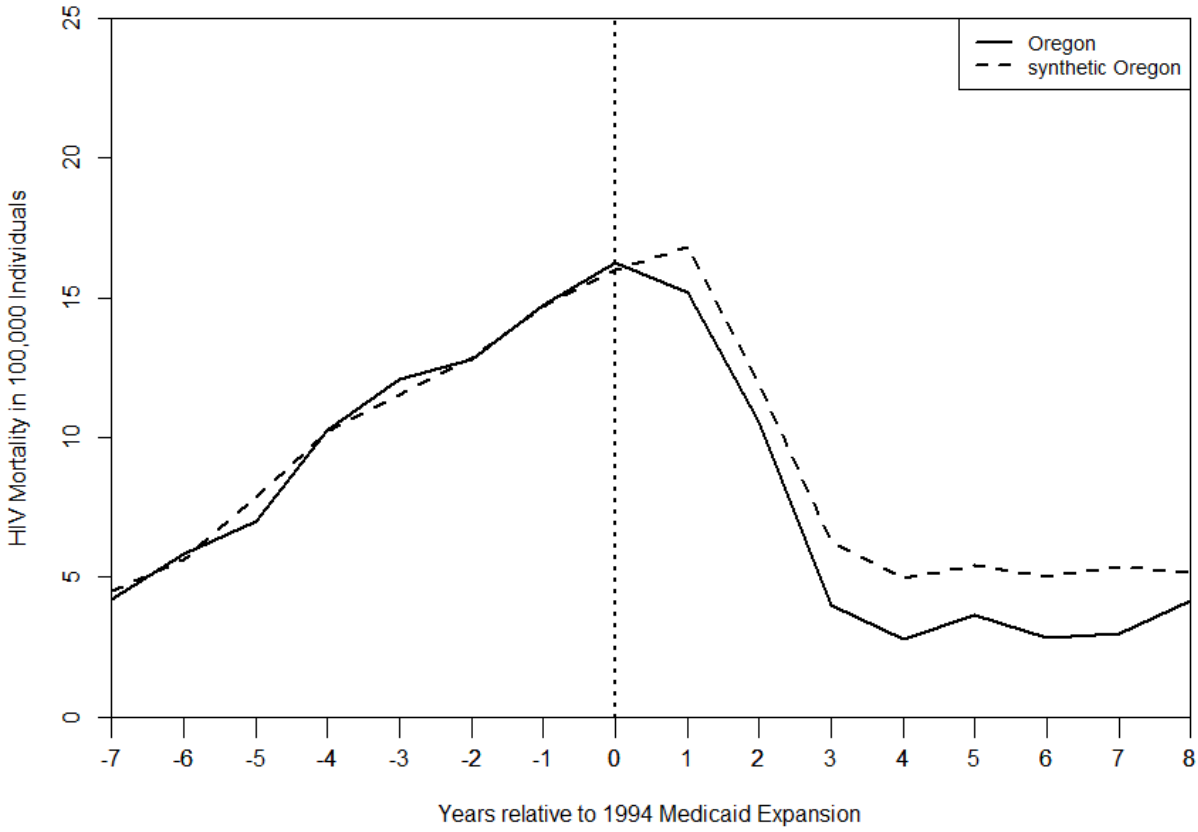


Figure B60: SCM OR HIV mortality rate counterfactual plot, 13 pre- and 8 post-treatment years