Estimating the Effects of the 2006 Massachusetts Health Care Reform on Health Coverage and Health Outcomes Using the Synthetic Control Method

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Abstract

This paper seeks to examine the effects of the 2006 Health Care Reform in Massachusetts, which established a common market to purchase health insurance, provided low-cost insurance for people ineligible for employer-sponsored health care, and expanded Medicaid coverage within the state prior to the 2010 passage of the Affordable Care Act. Past randomized controlled trials (RCTs) such as the RAND Health Insurance Experiment (1971-86) (13) and Oregon Medicaid Lottery (2009) (9) have found that reduced health care costs increased utilization of services without improving health outcomes. The purpose of this paper is to determine whether the effects of Massachusetts's Health Care Reform on health outcomes are consistent with the findings of these RCTs. Using the synthetic control method, I constructed a counterfactual for an event study examining the effect of the Massachusetts Health Care Reform on health insurance coverage and crude mortality rate. From 2006 to 2009, I found a statistically significant decrease in the share of uninsured individuals in Massachusetts by about 7.9 percent compared to the synthetic control. By 2009, private insurance coverage saw a statistically significant increase of about 3.76 percent, while Medicaid coverage increased by about 4.98 percent but was not found to be statistically significant after simulating a series of placebo effects and taking the rank of the mean squared prediction error. I also found a small, statistically insignificant decrease in the crude mortality rate by 19.75 deaths per 100,000 by 2008 and around 12.25 deaths per 100,000 by 2009. The implications of these findings can inform optimal implementation of market-oriented expansion of health coverage.

Keywords: health care reform; synthetic control method; econometrics; public policy

1 Introduction

Health care is evermore at the forefront of public policy discussion as well as one of the most important issues for voters in recent elections, per Pew Research Polling for the 2020 US Presidential Election. According to the US Census Bureau, 8.6 percent of people did not have any sort of health insurance coverage at any point in the year 2020, with 66.5 percent of those with health care coverage covered by private insurance, while 34.8 percent of those covered receiving a form of public insurance coverage. (Note that figures may not add up to 100 percent due to rounding errors). About 54.4 percent of private coverage was from employer-sponsored health insurance, while public plans were predominantly either recipients of Medicare (18.4 percent) or Medicaid (17.8 percent).

The reduction in rates of uninsurance in the past decade are largely attributable to the passage of the Affordable Care Act (ACA) in 2010. In addition to preventing insurance companies from denying patient coverage due to pre-existing conditions, the ACA, which required purchasing health insurance through an individual mandate at its inception, saw an increase of 11.3 million insured individuals through its establishment of a Health Insurance Marketplace, as well as an increase of 14.8 newly eligible recipients of Medicaid through expanded eligibility requirements. The decision by policymakers to include an individual mandate with the ACA is one that gained support within the Democratic party at least partially as a result of the purported success of a similar health care mandate in 2006 (11). The 2006 Massachusetts Health Care Reform, signed into law by then-Governor Mitt Romney and dubbed "Romneycare," made use of an individual mandate which required all Massachusetts residents to obtain a minimum level of health insurance coverage. In addition to expanding MassHealth, the state's public health insurance program which included Medicaid and State Children's Health Insurance Program (SCHIP), the law also subsidized health coverage for adults age 19 and older whose income was below 300 percent of the federal poverty level through its “Commonwealth Care” program, and established a common marketplace for Massachusetts residents to purchase private, unsubsidized health insurance independent of their employer.

With the passage of mandatory health insurance policies in the last two decades, there have been broader pushes among US policymakers and voters for further expansion of health insurance coverage. Most recently, President Joseph R. Biden ran on a platform of building upon the provisions of the ACA, seeking to “give Americans more choice” by maintaining the private insurance marketplace as well as expanding Medicaid requirements and increasing subsidized health care coverage through a public option. However, there remains the need for policymakers to be cognizant of the potential shortcomings of expanded health insurance coverage.

Evidence from previous randomized controlled trials (RCTs) indicates that despite increases in coverage, expanded health insurance programs increase utilization of services without necessarily improving health outcomes. From 1974 to 1982, RAND Corporation conducted their own RCT (the “RAND Health Insurance Experiment [HIE]”), in which they randomly assigned participants to health insurance plans with varying levels of cost-sharing; the most generous plans offered comprehensive care free of charge, while the least generous plans, besides a “catastrophic plan” which approximated a “no health insurance” control, required families to pay 95 percent of their health care costs. Despite increased utilization of health care services as a result of lower cost-sharing, participants on more generous plans did not have significantly better health outcomes on a set of baseline health variables (general health index, cholesterol levels, systolic blood pressure, and mental health index), worrying economists that generous health insurance plans can increase utilization and administrative costs without leading to improved health.

A second RCT took place in Oregon in 2008. Oregon randomly assigned expanded Medicaid coverage via a statewide lottery. While recipients of public insurance under the Medicaid expansion had higher self-reported health status compared to non-recipients, there were no statistically significant improvements on key health indicators such as systolic blood pressure and cholesterol levels. However, the results of the RCT did see modest improvement in mental health among recipients of expanded Medicaid coverage, likely due to stress relief from reduced financial burdens; yet, the Oregon Medicaid lottery once again demonstrated to researchers that increased health care coverage do not necessarily reap dividends in terms of improved health outcomes.

Based on the findings for these RCTs, cause for concern about moral hazard in health insurance have emerged among economists and policymakers, making health insurance expansion without cost-sharing a less appealing policy choice due to the risk of over-utilization of services without yielding improved health outcomes among patients. Indeed, a growing body of evidence studying the RAND HIE and Oregon Medicaid Lottery in addition to other quasi-experimental evidence finds that moral hazard in health care utilization and spending as a result of insurance increases “irrefutably exists” (Einav and Finklestein, 2018) (7) while additional evidence finds that moral hazard accounts for a majority of the increase in additional medical spending in the most generous health insurance plans (Powell and Goldman, 2016) (15).

In line with the existing literature on health insurance coverage and health outcomes, the purpose of this paper is to employ novel causal inference techniques to determine whether (1) the inclusion of an individual mandate in the 2006 Massachusetts Health Care Reform did, in fact, lead to a statistically significant decrease in uninsurance rates, and (2) whether expanded coverage reduced the state’s crude mortality rate as a measure of improved health outcomes.

2 Methodology

Causal inference as a study tasks itself with determining how a given set of variables or intervention *cause* a given outcome of interest. In other words, it seeks to determine how one or more variables directly influence the outcome of another variable, as opposed to just determining whether these variables are correlated. Traditionally, causality is best established through experimental evidence with RCTs, which allow researchers to leverage comparisons between an assigned treatment group and control group to isolate the effects of independent variables on outcome variables, *ceteris paribus.* At the policy level, though, “treatment” and “control” groups are not randomly assigned, and proper “control” groups rarely exist, at all. For a variety of practical and ethical reasons, when policy is passed, everyone in a given locale is affected by the policy, making it difficult to ascertain the causal effects of said policy on the affected population.

In lieu of RCTs, causal inference for event studies has traditionally been conducted via a “natural experiment” approach using difference-in-differences to estimate the effects of policy interventions, where typically, the effects of policy passed in one city or state are compared to a “control” group consisting of a neighboring city or state. One prominent paper which spear-headed the “credibility revolution” in economics employed difference-in-differences methodology to study the disemployment effects of a minimum wage increase in New

Jersey by comparing employment growth in fast-food restaurants to neighboring eastern Pennsylvania, where the minimum wage was not increased, finding no significant increase in unemployment in New Jersey (Card and Krueger, 1994) (6). This approach effectively creates quasi-experimental evidence with a treatment and control group, but is not without its downsides. Difference-in-differences makes several key assumptions which might not hold true or introduce bias into difference-in-differences models. For examples, difference-in-differences assumes that the intervention is unrelated to the outcome of interest; that there is a parallel trend in the outcome variable between the treatment and control group; that the composition of the treatment and control group is stable over time; and that the observed variables have no spillover effects. Failure to meet these assumptions introduces issues with unobserved confounders, reverse causality, and omitted variable bias.

However, with an increasing body of economic literature employing causal inference with the synthetic control method (SCM), described as "arguably the most important innovation in the policy evaluation literature in the last 15 years" (Athey and Imbens, 2017) (5), many of the assumptions behind traditional difference-in-differences methodology are able to be relaxed while reducing the incidence of unobserved confounders (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Abadie et al., 2014) (1) (2) (3). Rather than a single city, state, or other locale serving as the "control" group, the SCM leverages a large "donor pool" that is used to synthetically construct a counterfactual estimate for the study under the assumption that the treatment group pre-intervention can be expressed as a linear combination of all the non-treated groups in the donor pool, matched on a set of covariates. The SCM also utilizes selected lagged outcome variables which reduce the possibility of time-related confounders or omitted predictor effects, and these time lags are so powerful at reducing bias in and of themselves that often, other covariates hardly matter (Athey and Imbens, 2006) (4). The non-treated regions in the donor pool are then assigned weights summing to 1 which minimize the outcome's root mean squared prediction error prior to treatment, constructing a counterfactual estimate that "fits" the treatment region very well prior to any intervention. The assumptions for the SCM are as follows: no region in the donor pool can undergo a similar policy intervention; the policy in the affected region cannot affect the outcomes in any of the regions in the donor pool; the predictor variables used to construct the weights must be similar in both the treated region and regions in the donor pool; and the values for the predictor variables in the treated region must be able to be expressed as a linear combination of the predictor variables in regions in the donor pool.

3 Dataset description

I draw upon individual- and household-level microdata data gathered between 2001 and 2010 from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), one of the oldest and largest surveys in the US representative of the civilian household-based population (8). Since survey questions inquire about information from the previous year for each respondent, the dataset I have gathered represents information from 2000 to 2009, prior to the passage of the ACA. For the purposes of the synthetic control implementation, I examined the time-related effects on uninsurance rates in Massachusetts, the "treatment" state, compared to other US states, the "control" states. I elected to exclude Hawaii and Oregon from the control group. Hawaii implemented a mandatory health insurance program in 1975, meaning data from Hawaii would not constitute a proper control group unaffected by implementation of insurance mandates. Oregon conducted their Medicaid lottery between 2008 and 2009, expanding Medicaid coverage in the state. Thus, Oregon, similar to Hawaii, does not constitute a proper "control" group unaffected by health insurance expansion. I then matched Massachusetts to the control group on a set of covariates: the share of the state population in good health (I opted to consider survey responses of a 3 or higher on a 5-point scale of self-reported health status as "in good health"); median household income; mean age; unemployment rate; female population share; Hispanic population share; married population share; citizenship population share; share of state residents below the poverty line; and the share of the population who have an educational attainment of a high-school diploma or higher. Since the Massachusetts Health Care Reform only expanded private insurance and Medicaid coverage but did not expand Medicare or Veterans' Health Care Coverage, I restricted my sample to non-veterans aged 19 to 64, only analyzing the effect of the health insurance expansion on adult, non-veteran, non-elderly recipients of private insurance or Medicaid coverage. (Note that this analysis therefore excludes children from the sample, who were beneficiaries of expanded SCHIP provisions.) While survey microdata on health outcomes is not available as state-level data through the National Health Interview Survey (NHIS) accompanying the CPS, I utilized crude mortality rate data from the CDC Wonder Database, grouping the data by state and restricting the sample to individuals aged 19 to 64 to match the dataset from the CPS. Employing primarily the pandas library in the Python programming language, I grouped CPS sample aggregates by state and join the dataset with similarly grouped data from CDC Wonder to generate my final dataset.

4 Synthetic Control Model

Suppose we have $J + 1$ units where $j = 1$ represents the treated unit and $j = 2, 3, ..., J, J + 1$ are untreated units from the donor pool. For each unit j, let Y_{jt} be the outcome of interest for each unit j and time period t

across T time periods, with T_0 representing the intervention time. As such, the treatment effect τ on $j = 1$ at time t can be expressed as the difference in the potential outcome of the treated units Y_{1t} and the non-treated units Y_{jt}^N, hence $\tau_{1t} = Y_{1t} - Y_{jt}^N$. To estimate the non-treatment effect, we will consider $\hat{Y}_{jt}^N$ to be measured as the outcome of interest Y_{jt} for treated units j = 2, 3, ..., J, $J + 1$ at time t, with a vector $\vec{w}_j^*$ as a set of optimally chosen weights which minimize the root mean squared prediction error. Therefore, the synthetic control estimator which models the effect of the intervention at T_0 measures the causal effect in the post-treatment period as

$$\tau_{1t} = Y_{1t} - \sum_{j=2}^{J+1} \vec{w}_j^* Y_{jt}$$

For matched variable matrices X_0 and X_1 containing predictors of post-intervention outcomes, to find $\vec{w}_j^*$, a vector of weights W must be selected such that $W = (w_2, w_3, ..., w_J, w_J + 1)'$ with $w_j \geq 0$ and $\sum_{j=2}^{J+1} w_j = 1$. Therefore, the norm

$$||X_0 - X_1 W|| = \sqrt{(X_0 - X_1 W)' V (X_0 - X_1 W)}$$

where V is a $k \times k$ positive, semi-definite diagonal matrix whose entries along the diagonal $v_1, ..., v_k$ reflect the predictive value of covariates. V is chosen such that the matrix product $W^* V$ minimizes the mean squared prediction error

$$\sum_{t=1}^{T_0} (Y_{1t} - \sum_{j=2}^{J+1} \vec{w}_j^* V Y_{jt})^2$$

Therefore, the set of weights $W = (w_2, w_3, ..., w_J, w_J + 1)$ which minimizes the root mean squared prediction error is

$$||X_0 - X_1 W|| = \sqrt{\sum_{t=1}^{T_0} (Y_{1t} - \sum_{j=2}^{J+1} \vec{w}_j^* V Y_{jt})^2}$$

5 Results

An exploratory data analysis (EDA) of the CPS sample revealed that in 2006, about 11.48 percent of non-veteran, non-elderly Massachusetts adults were uninsured. Among those who were insured, about 77.5 percent were covered by private insurance, while 11.5 percent were covered by Medicaid.

Following the EDA, I constructed four separate synthetic control models.

In Model A, the outcome variable of interest Y_{jtA} is the uninsurance rate per 100,000 for all insurance plans for the treated unit $j = 1$ being Massachusetts and j = 2, 3, ..., 49 being the donor pool of all US states minus Hawaii and Oregon plus the District of Columbia. I selected a covariate matrix X for both the treatment and control group, with all variables measured in units per 100,000 (except for income and age), representing self-reported health status, median household income, mean age, unemployment rate, poverty rate, educational attainment, and several key demographic variables (sex, Hispanic origin, marital status, citizenship status). I also used a set of 4 lagged variables: the uninsurance rate in 2000, 2002, 2004, and 2006. The optimal set of weights such that the root mean squared prediction error is minimized is $w_{23} = 0.470$, $w_{38} = 0.313$, $w_{10} = 0.109$, and $w_{16} = 0.106$. These weights represent the corresponding states which form the synthetic Massachusetts:

Table 1: Donor pool state and corresponding weight (Model A)

State	Weight
Minnesota	0.470
Rhode Island	0.313
District of Columbia	0.109
Iowa	0.106

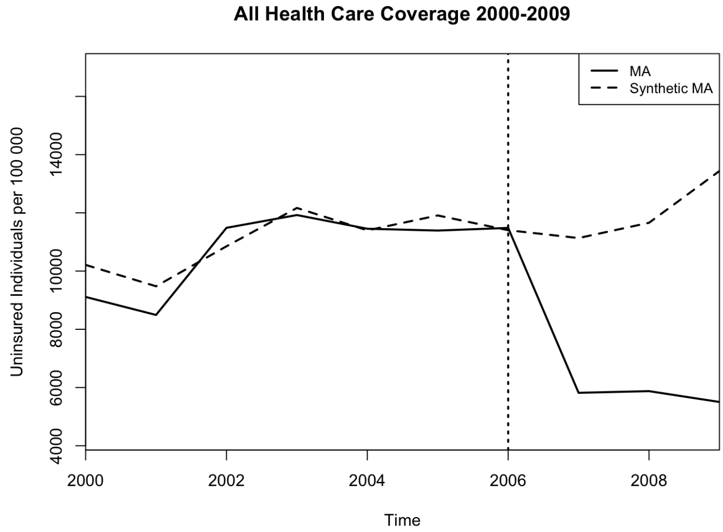

Figure 1: Uninsurance Rate Per 100,000 in Massachusetts vs. Synthetic Massachusetts (2000-2009)

The treatment effect τ_{1tA} can therefore be expressed as the gap between the treated unit, Y_{1tA} for $j = 1$ (Massachusetts), and the synthetic control, which is approximated using the state weights from Table 1 as $w_{10}\,Y_{10tA} + w_{16}\,Y_{16tA} + w_{23}\,Y_{23tA} + w_{38}\,Y_{38tA}$.

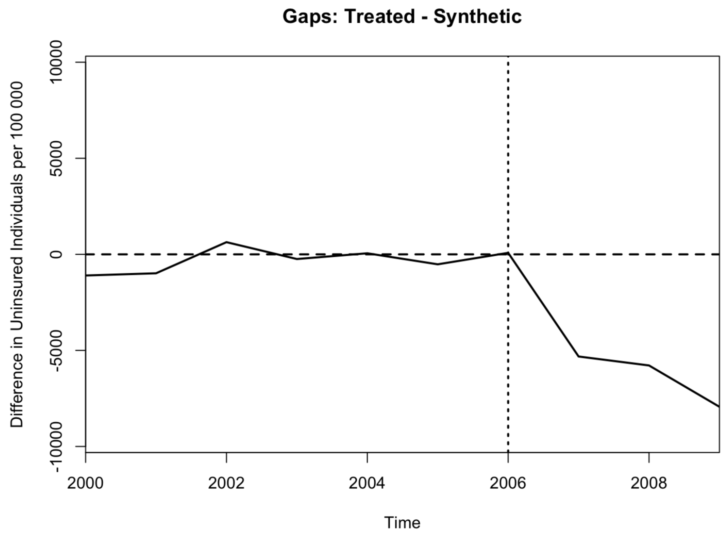

Figure 2: Gap in Uninsurance Rate in Massachusetts vs. Synthetic Massachusetts (2000-2009)

These results show that per 100,000, about 7,900 fewer individuals were uninsured in Massachusetts by 2009 compared to the synthetic control, or a reduction in the uninsurance rate of 7.9 percent over the three-year period after the health reform was passed.

While this method gives the effect size of the treatment, it does not tell us whether the observed difference is statistically significant. It could be that the divergence in the treated unit and control unit is simply a result of prediction error that any model would have selected for; in other words, the divergence may represent a "placebo effect" where any model would show a sizable difference between the treated and control units even if the treatment had no effect. Abadie et al. (2010) (1) propose a falsification check using Fisher's exact test to construct p-values for both the treated and control units. Let

$$H_0 : \text{No treatment effect whatsoever}$$

$$H_A : \text{There is a treatment effect as a result of the intervention}$$

By iteratively applying the SCM to each control unit in the donor pool, I obtained a distribution of placebo effects which showed the divergence between the placebo units and their respective control units when no true treatment effect is in place. Abadie et al. (2010) (1) then propose sorting, in descending order, each placebo by the ratio of the mean squared prediction error post- to pre-intervention, and calculating the p-value as the proportion of times the effect in the treated unit is larger than the effect in the placebo units

$$\frac{1}{N}\sum 1\{\hat{\tau_1} > \hat{\tau_j}\} = \frac{\text{Treated Rank}}{\text{Total Number of Units}}.$$

Below is the placebo distribution comparing the control units to Census STATEFIP 25, which represents Massachusetts, as well as the histogram of the post/pre-MSPE ratio.

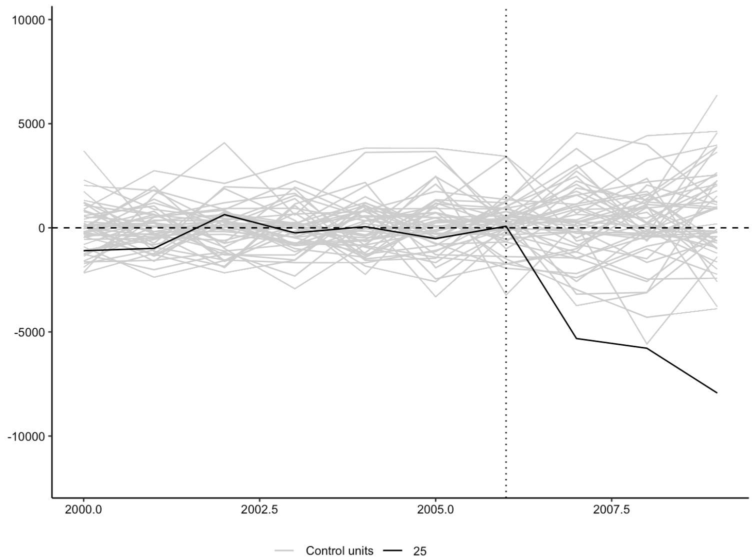

Figure 3: Distribution of Placebo Effects, Model A (2000-2009)

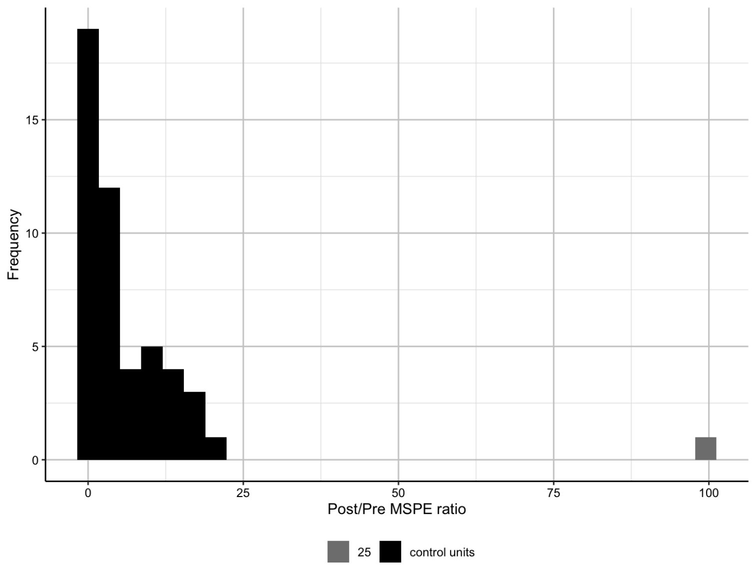

Figure 4: Histogram of Post-/Pre-MSPE Ratio, Model A (2000-2009)

Massachusetts ranked first in post/pre-MSPE ratio among 49 total units, yielding a p-value of 0.02. At the $\alpha = 0.05$ significance level, I reject H_0 in favor of H_A. The Massachusetts Health Care Reform had a statistically significant effect on decreasing the share of individuals aged 19-64 without health insurance.

I repeated the same procedure to calculate the effect size and significance level of private insurance coverage (Model B) and Medicaid coverage (Model C) per 100,000 as a result of the Massachusetts Health Care Reform, using the same set of covariates and lagged treatment outcomes to match the treatment and control groups.

Table 2: Donor pool state and corresponding weight (Model B)

State	Weight
Connecticut	0.554
New Jersey	0.166
Arizona	0.0822
District of Columbia	0.0715
Vermont	0.0620
Minnesota	0.0533

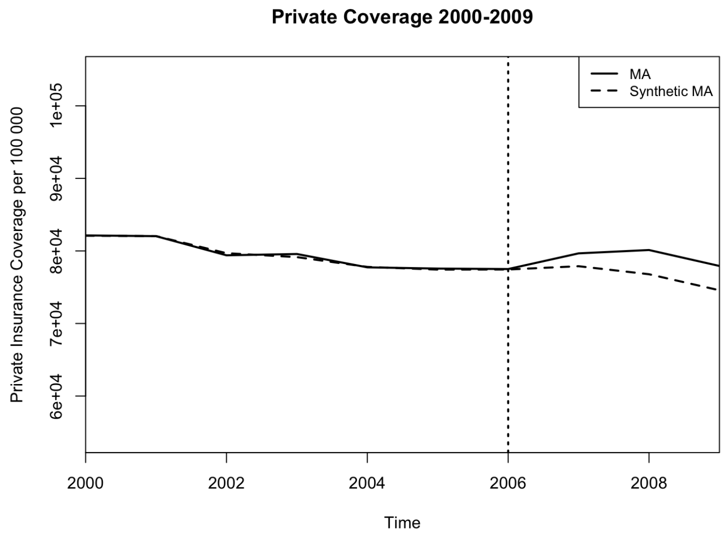

Figure 5: Private Coverage per 100,000 in Massachusetts vs. Synthetic Massachusetts (2000-2009)

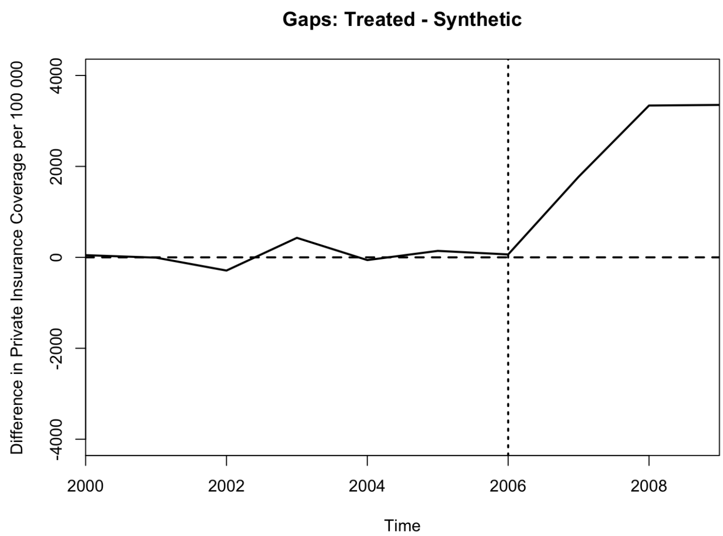

Figure 6: Gap in Private Coverage Rate in Massachusetts vs. Synthetic Massachusetts (2000-2009)

These results show that per 100,000, 3,760 more individuals received private insurance coverage in Massachusetts by 2009 compared to the synthetic control, or an increase of 3.76 percent over the three-year period after the health reform was passed.

Simulating placebos under Fisher's exact test and ranking placebo effects by the ratio of post-/pre-MSPE:

$$H_0 : \text{No treatment effect whatsoever}$$

$$H_A : \text{There is a treatment effect as a result of the intervention}$$

$$p\text{-value} = \frac{1}{N}\sum 1\{\hat{\tau}_1 > \hat{\tau}_j\} = \frac{\text{Treated Rank}}{\text{Total Number of Units}}.$$

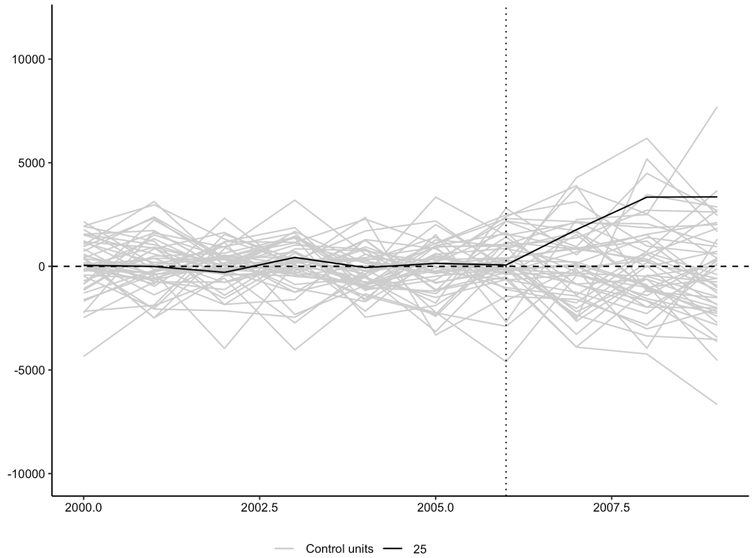

Figure 7: Distribution of Placebo Effects, Model B (2000-2009)

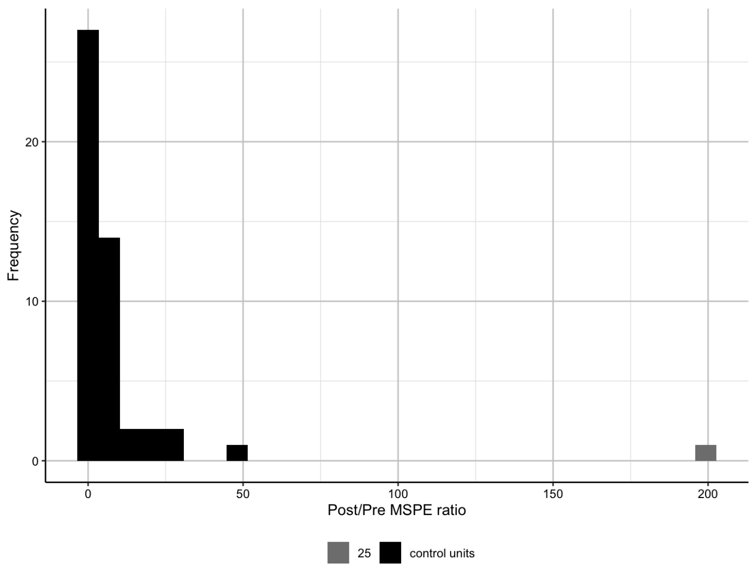

Figure 8: Histogram of Post-/Pre-MSPE Ratio, Model B (2000-2009)

For private insurance coverage, Massachusetts (STATEFIP = 25) ranked first in post/pre-MSPE ratio among 49 total units, yielding a p-value of 0.02. At the $\alpha = 0.05$ significance level, I reject H_0 in favor of H_A. The Massachusetts Health Care Reform, through its creation of a common marketplace to purchase health insurance independent of an employer, seems to have had a statistically significant effect on increasing private insurance coverage for individuals aged 19-64.

Treatment effect size for Medicaid coverage (Model C):

Table 3: Donor pool state and corresponding weight (Model C)

State	Weight
Vermont	0.427
California	0.150
Rhode Island	0.148
New Jersey	0.131
District of Columbia	0.0510
Minnesota	0.0219

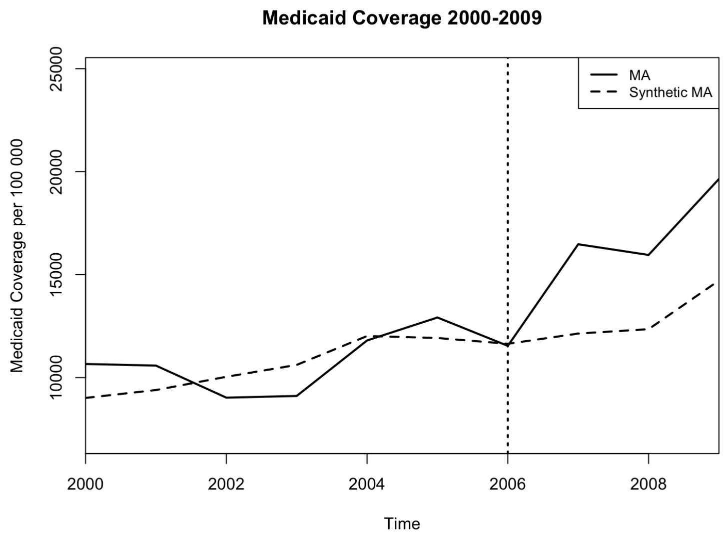

Figure 9: Medicaid Coverage per 100,000 in Massachusetts vs. Synthetic Massachusetts (2000-2009)

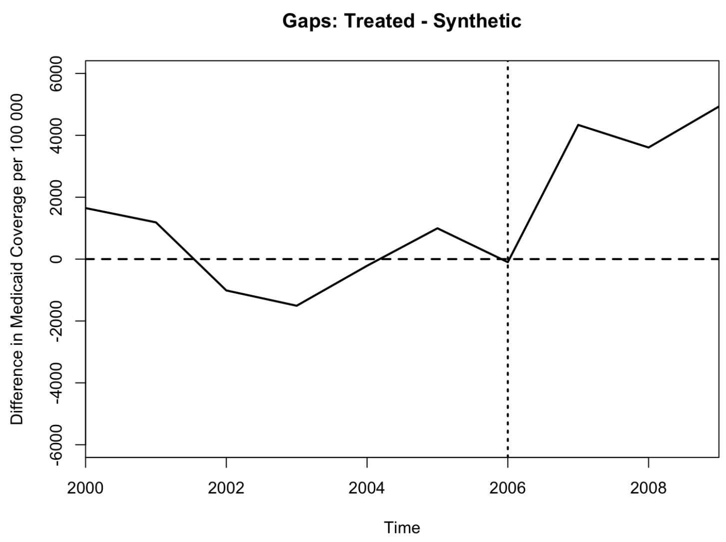

Figure 10: Gap in Medicaid Coverage Rate in Massachusetts vs. Synthetic Massachusetts (2000-2009)

These results show that per 100,000, 4,980 more individuals received Medicaid coverage in Massachusetts by 2009 compared to the synthetic control, or an increase of 4.98 percent over the three-year period after the health reform was passed.

Simulating placebos under Fisher's exact test and ranking placebo effects by the ratio of post-/pre-MSPE:

$$H_0 : \text{No treatment effect whatsoever}$$

$$H_A : \text{There is a treatment effect as a result of the intervention}$$

$$p\text{-value} = \frac{1}{N}\sum 1\{\hat{\tau}_1 > \hat{\tau}_j\} = \frac{\text{Treated Rank}}{\text{Total Number of Units}}.$$

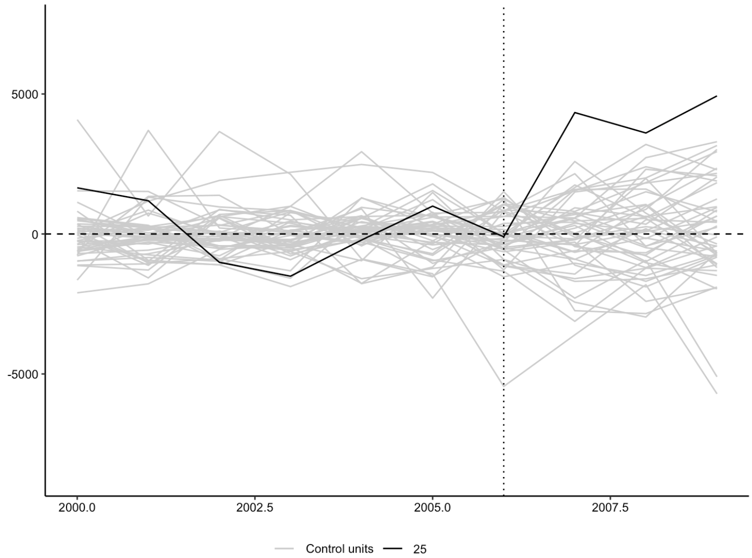

Figure 11: Distribution of Placebo Effects, Model C (2000-2009)

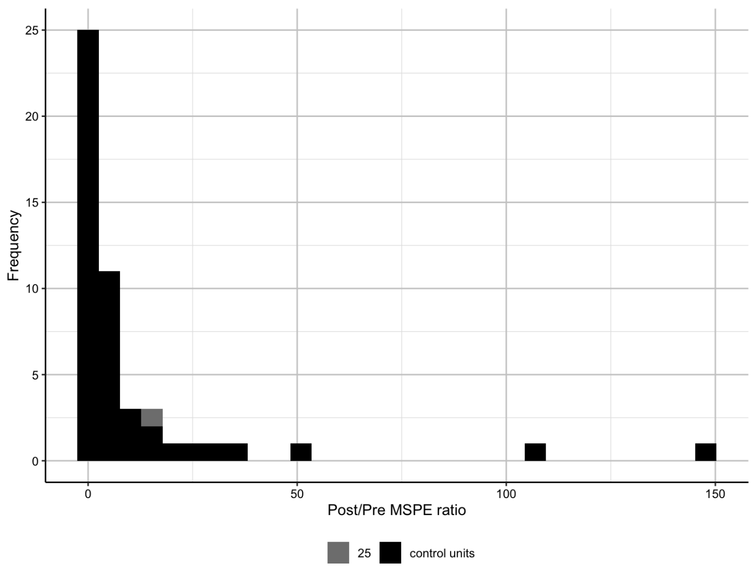

Figure 12: Histogram of Post-/Pre-MSPE Ratio, Model C (2000-2009)

For Medicaid coverage, Massachusetts (STATEFIP = 25) was tied for tenth in post/pre-MSPE ratio among 49 total units, yielding a p-value of 0.204. At the $\alpha = 0.05$ significance level, I fail to reject H_0. Based on the effect size of the treatment, Massachusetts did see an increase in individuals covered by Medicaid after the passage of the Health Care Reform, but this seems to be due to the existence of some sort of placebo; in other words, Medicaid coverage increased in Massachusetts for reasons other than the Health Care Reform, and any model would have shown an increase. One plausible reason for this could be the impact of the Great Recession. Evidence from Alabama shows that a one percent increase in a county's unemployment rate was associated with a 4.3 increase in Medicaid enrollment (Morrisey et al., 2016) (14), meaning that due to an increase in unemployment in several states, more people were eligible for Medicaid despite no statewide health care reforms. Thus, the Massachusetts Health Care Reform seems not to have had a statistically significant causal effect on increasing Medicaid coverage for individuals aged 19-64.

These models provide evidence that the 2006 Massachusetts Health Care Reform did increase overall health care coverage among the state's non-elderly adult residents. I then constructed a synthetic control model, Model D, for the effect of the expansion in health coverage as a result of the reform on health outcomes, measured by the state's crude mortality rate per 100,000 among adults aged 19-64. The chosen covariate matrix X for both the treatment and control group, with all variables measured in units per 100,000 (except for income and age), includes median household income, mean age, unemployment rate, poverty rate, educational attainment, and several key demographic variables (sex, Hispanic origin, marital status, citizenship status), in addition to a set of 4 lagged variables: the crude mortality rate rate in 2000, 2002, 2004, and 2006. The optimal set of weights such that the root mean squared prediction error is minimized is $w_{38} = 0.543$, $w_{23} = 0.283$, $w_{32} = 0.120$, and $w_8 = 0.0488$. These weights represent the corresponding states which form the synthetic Massachusetts:

Table 4: Donor pool state and corresponding weight (Model D)

State	Weight
Rhode Island	0.543
Minnesota	0.283
New York	0.120
Connecticut	0.0488

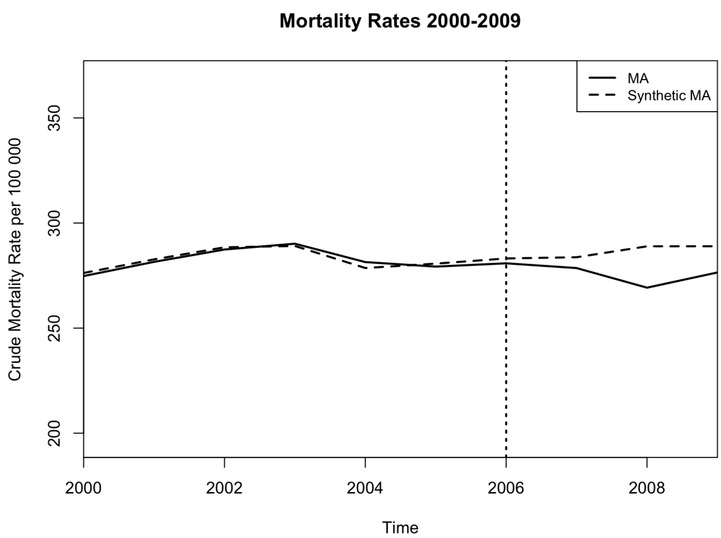

Figure 13: Crude Mortality Rate per 100,000 in Massachusetts vs. Synthetic Massachusetts (2000-2009)

We can model the treatment effect on crude mortality rate, approximating the non-treated unit with the weights from Table 4, as $\tau_{1tD} = Y_{1tD} - (w_8 Y_{8tD} + w_{23} Y_{23tD} + w_{32} Y_{32tD} + w_{38D} Y_{38tD})$.

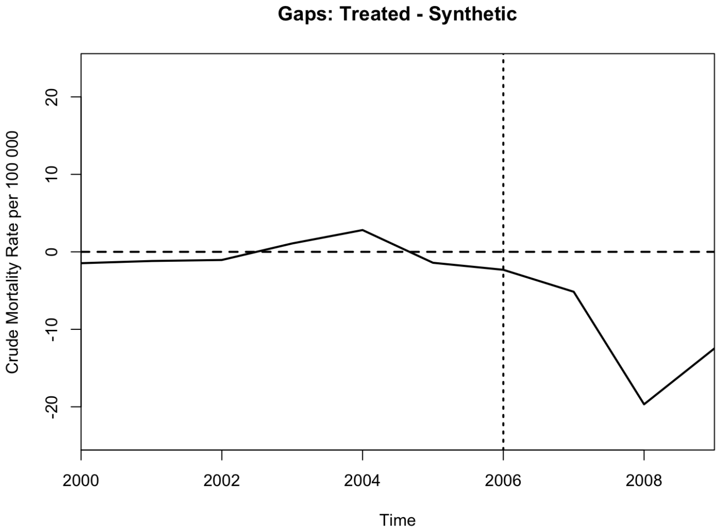

Figure 14: Gap in Crude Mortality Rate in Massachusetts vs. Synthetic Massachusetts (2000-2009)

These results show that at its lowest, the crude mortality rate per 100,000 declined by 19.75 by 2008 compared to the synthetic control, or a decrease of about 0.02 percent in the first two years of the reform. By 2009, the crude mortality rate decreased by 12.25 per 100,000 relative to when the reform was passed in 2006, representing a reduction in the crude mortality rate of about 0.01 percent compared to the synthetic control.

While the effect size appears to be small, whether the decline is statistically significant remains unanswered. I once again simulated placebos under Fisher's exact test and rank the placebo effects by the post-/pre-MSPE ratio.

$$H_0 : \text{No treatment effect whatsoever}$$

$$H_A : \text{There is a treatment effect as a result of the intervention}$$

$$p\text{-value} = \frac{1}{N}\sum 1\{\hat{\tau}_1 > \hat{\tau}_j\} = \frac{\text{Treated Rank}}{\text{Total Number of Units}}.$$

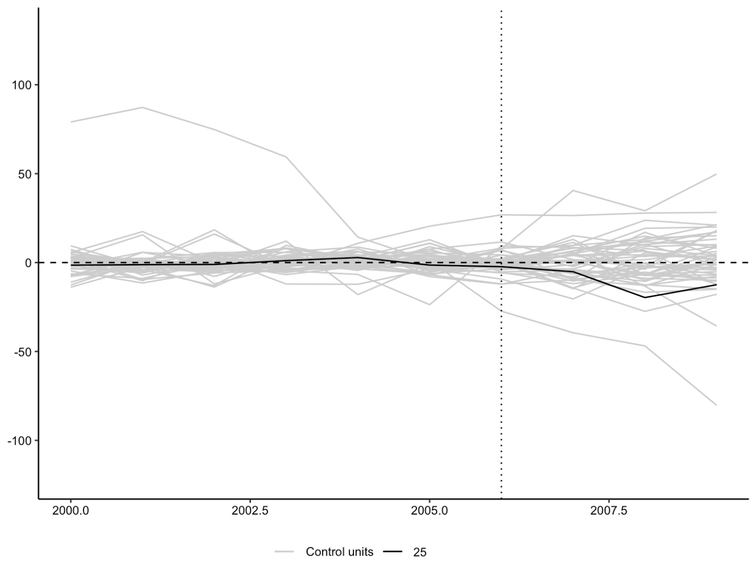

Figure 15: Distribution of Placebo Effects, Model D (2000-2009)

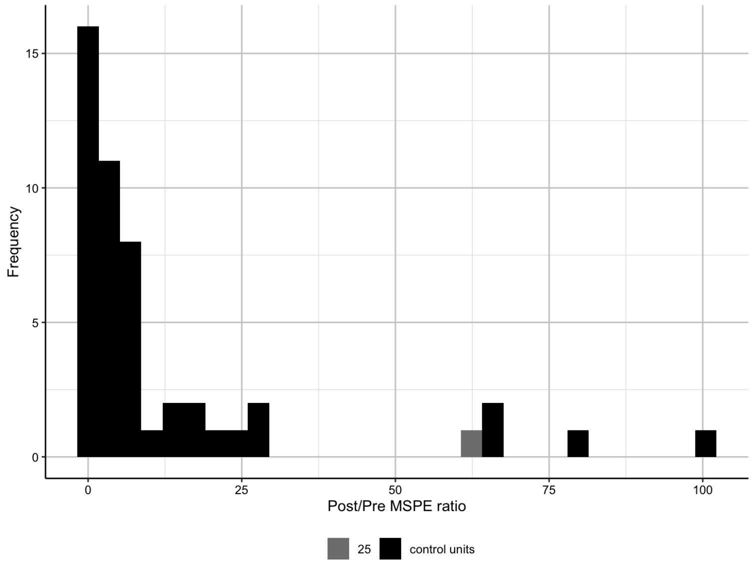

Figure 16: Histogram of Post-/Pre-MSPE Ratio, Model D (2000-2009)

Massachusetts ranked fifth in post/pre-MSPE ratio among 49 total units, giving a p-value of 0.102. At the $\alpha = 0.05$ significance level, I fail to reject H_0. Despite gains in health insurance expansion in the state, the 2006 Massachusetts Health Care Reform seems to not have had a statistically significant effect on the crude mortality rate.

6 Conclusion

The findings from this paper are consistent with the findings from both the RAND HIE and Oregon Medicaid Lottery. Despite a large, statistically significant increase ($p < 0.05$) in overall health coverage given the decline in uninsurance rates from 2006 to 2009, these coverage gains from the 2006 Massachusetts Health Care Reform did not translate to a statistically significant dividend in the form of reduced crude mortality rates. While the establishment of a common marketplace to purchase private insurance for individuals without employer-sponsored health coverage did see a statistically significant ($p < 0.05$) increase in the share of individuals covered by private insurance, the gains in Medicaid expansion do not seem to be statistically significant. While Medicaid coverage did increase, the results from the placebo simulation seem to indicate that Medicaid coverage may have increased for reasons other than the health care reform as the model demonstrated similar gains in non-treatment states. The reason for this might have to do with an increase in enrollment in state Medicaid programs following the Great Recession between 2007 and 2009 among newly unemployed individuals (Morrisey et al. 2016) (14).

The implications of these results continue to underscore the importance for policymakers to address moral hazard when implementing reforms to the medical system that increase coverage. Since the 2006 reform seems to have increased coverage without necessarily leading to a statistically significant decline in the mortality rate, policymakers must be cautious of the potential increase in administrative costs on a health care system that sees an increase in utilization of services due to less cost-sharing without leading to improved outcomes.

These results should be interpreted with caution and within the context of the dataset. The expansion of eligibility in Massachusett's SCHIP program may have increased coverage for children, an effect which was not studied within the contents of this paper. Additionally, while overall mortality rate may not have decreased to a statistically significant degree, there may have been improvements in other key health indicators such as blood pressure, cholesterol levels, or mental health which were not captured by the measure of health outcomes. Finally, due to the limitations of both CPS and CDC Wonder datasets, as well as the difficult of accessing medical records with state-level data, I was unable to test for a change in health expenditures or health services utilization as a result of the 2006 reform. For example, there is evidence that personal medical expenditures and medical bankruptcies may have increased despite the reform, although this may have also been due to the Great Recession (Lusk, 2011; Joynt et al., 2015) (12) (10). Since the reform was really only in effect for three years before health care plans under its provisions were transferred over to ACA provisions, the long-term effects of the 2006 Massachusetts Health Care Reform cannot be definitively concluded.

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