The Impact of Individual Mandate on High-Income, Non-elderly Individual Health Insurance Coverage Rates and Racial/Ethnic Disparities

YeJin Ahn

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Abstract

The purpose of this paper is to assess the impacts of the individual mandate in the Affordable Care Act on health insurance coverage for individuals under age 65 and with incomes above 400% of federal poverty level. I use data from the 2014-2019 American Community Survey. My methods feature a difference-in-differences model, event-study, and synthetic control, exploiting the variation in state individual mandate status. I further stratify my sample by race/ethnicity and run coverage gap regressions to examine the policy's effect on racial/ethnic disparities. Using data for one year after the mandates are in place, I find that the mandate had a small, positive effect on health insurance coverage with mixed statistical significance and reduced racial/ethnic coverage disparities.

The individual shared responsibility provision, commonly known as the individual mandate, has always been a controversial feature of the Affordable Care Act (ACA). It requires that individuals have health insurance or pay a penalty. While the Supreme Court decided the individual mandate was constitutional (*National Federation of Independent Business v. Sebelius*), opponents argued that it is an encroachment of individual liberty and coercive action by the government. Proponents, on the other hand, have argued that it expands insurance coverage and increases the pooling of health care spending burdens among the healthy and sick. In theory, the additional health insurance enrollment, especially among the healthy, will decrease without the mandate. Insurers will respond to this adverse selection by increasing premiums, which will in turn further reduce enrollment.

The 2017 Tax Cuts and Jobs Act essentially eliminated the individual mandate by reducing the penalty to $0 beginning in 2019. In response, New Jersey and the District of Columbia (D.C.) enacted a state-level individual mandate that closely resembles the federal rules, taking effect also at the start of 2019.

There has been a lack of literature on its effect on insurance coverage mainly due to multiple provisions of ACA being implemented simultaneously. Additionally, there are some disagreements among researchers with most suggesting an increase in coverage (Fung et al. 2019; Hackmann, Kolstad, Kowalski 2015; Jacobs 2018; CBO 2019) while some showing small and inconsistent effect of mandate (Frean et al. 2017). In decomposing the effect of the individual mandate by race/ethnicity, there has been even more limited literature. Many studies have analyzed the impact of healthcare policies such as ACA and Medicaid expansions as a whole, but not specifically the individual mandate's effect by race/ethnicity. Among them, the racial coverage disparity decreased (Buchmueller et al. 2016; Courtemanche et al. 2019a; Courtemanche et al. 2019b; Sommers 2015) or increased (Angier et al. 2017; Yue et al. 2018) depending on the focus of income groups. Moreover, there has been no paper that focuses on high-income individuals to examine the racial/ethnic disparities.

Understanding such effects is critical for several reasons. First, it tests whether the mandate works as the theory predicts. Second, health insurance is crucial in helping people receive the medical care they need to maintain good health. Third, the mandate might disproportionately affect certain racial/ethnic groups (e.g., Hispanic individuals, Non-Hispanic Blacks).

My paper is the first study to look at the repeal of individual mandate at the federal level and implementation of state mandates in New Jersey and Washington D.C.. Additionally, it adds to the literature and provides insight into this important and controversial policy component of ACA with an initial attempt to directly analyze the effect of the individual mandate on coverage rates, further decompose the effect by race/ethnicity, and examine the effect on coverage gaps among high-income individuals. To isolate the effect of the individual mandate, I focus on individuals under age 65 and with household income above 400 percent of the federal poverty level (FPL). By focusing on this group, I identify a group that faces the individual mandate but is not eligible for the ACA’s subsidies. Additionally, recent empirical evidence concludes that the mandate may not be as important for lower income individuals as theory suggests due to high subsidies and Medicaid expansion (Kliff 2020), but fewer studies are conducted on whether the mandate has an effect on high-income groups that are not eligible for both.

When the repeal of individual mandate became effective in all states in 2019, New Jersey and D.C. implemented a state individual mandate while other states did not. Using the 2014-2019 American Community Survey (ACS) and Bureau of Labor Statistics (BLS) data, I exploit this state-level variation and use difference-in-differences (DD), event-study, and synthetic control models to first compare the overall coverage rates between states with individual mandates (New

Jersey and D.C.) and states without, then compare them among different racial/ethnic groups. Furthermore, I implement coverage gap regressions to further examine the impact of the state mandate on racial/ethnic disparities. However, as there are limited post-2019 data, I am only able to capture the short-term effect.

I hypothesize that the state individual mandate will increase coverage rates among high-income, non-elderly individuals. Moreover, I hypothesize that it will decrease the racial/ethnic disparity (Non-Hispanic Whites versus Non-Hispanic Blacks and Hispanics) in coverage rates. I use a main DD model and a model that also adds unemployment rate as a control. Both are analyzed in a pooled (New Jersey and Washington D.C.) sample, then each state separately. Using the main pooled model, I find that the state individual mandate had a statistically significant, positive effect on health insurance coverage. Adding unemployment rate to the pooled model, I find that the state individual mandate had a positive, but statistically insignificant, effect on health insurance coverage. When analyzing the states separately, for New Jersey I find results qualitatively similar to the pooled sample – positive and statistically significant but insignificant when I add unemployment rate. For Washington D.C., the effect of mandates remains positive and statistically significant with and without the unemployment rate. To use a data driven approach to address the control group, I use a synthetic control method separately for New Jersey and Washington D.C.. I find a negative effect on coverage, but both are statistically insignificant.

Stratifying the DD models by different racial/ethnic groups, I find that the racial/ethnic coverage disparity is reduced but by a small amount. The main model suggests that the largest increase is among Hispanics, then Non-Hispanic Blacks, Non-Hispanic Whites, and Non-Hispanic other races. Results for all racial/ethnic groups are statistically significant. Adding unemployment rate, Non-Hispanic Blacks experienced a larger increase in health insurance coverage than Non-

Hispanic Whites, and Hispanics and Non-Hispanic other races experienced a smaller increase. The results are statistically significant for Non-Hispanic Blacks and Non-Hispanic Whites, while statistically insignificant for Hispanics and Non-Hispanic other races. Lastly, I find that the state mandate had a small effect on the Black-White and Hispanic-White coverage gaps. By running the DD regression models in a placebo group, I find that my results are robust.

The remainder of this paper proceeds as follows. Section 1 describes the institutional background of the individual mandate. Section 2 reviews the literature on the effect of state individual mandate on health insurance coverage and racial/ethnic disparities. Section 3 describes data and main variables. Section 4 presents the study methodology and econometric specifications. Section 5 presents and discusses the results. Section 6 checks the robustness of the results and extends the DD regression models. Section 7 concludes with summary of results, limitations, directions for further research, and policy implications.

I. Institutional Background

The Patient Protection and Affordable Care Act (ACA) was signed into law on March 23, 2010. In January 2014, several provisions of the law aimed to reduce the number of uninsured, one of the ACA's primary goals. The provisions assisted individuals in various ways based on FPL. To help pay the monthly insurance premiums, individuals with household incomes between 100 and 400 percent of the FPL were provided with subsidies if they bought insurance on their own in the private health insurance market. Individuals earning over 400 percent of FPL did not qualify for subsidies. The ACA also allowed states to expand Medicaid to cover all non-elderly adults with incomes below or equal to 138 percent of FPL. To encourage people, especially the healthy, to purchase health insurance, an individual mandate penalty was imposed on individuals without insurance. It phased in starting in 2014, which reached the greater of $695 per adult ($347.50 per child) or 2.5 percent of income above filing threshold in 2016 and was capped at the national average cost of a marketplace bronze plan. There were several exemptions from the individual mandate, including elderly individuals at or above age 65, people with income below the tax filing threshold, people with income below 138 percent of FPL and live in a state that did not expand Medicaid, and people who would have to pay more than 8 percent of income (with the 8 percent adjusted over time), among others.

However, the Tax Cut and Jobs Act of 2017 repealed the ACA's federal mandate, beginning on January 1, 2019. Following the passage of the law, states responded with a mandate at the state level. Massachusetts's mandate, which was part of its 2006 health reform, remained in effect. New Jersey and D.C. enacted a state individual mandate with rules similar to the federal rules, both taking effect on January 1, 2019. Rhode Island, Vermont, and California enacted a mandate effective January 1, 2020, although Vermont had no financial penalty attached to the mandate.

In addition to the provisions and revisions of ACA, an Executive Order (EO) 13813 "Promoting Healthcare Choice and Competition Across the United States" was signed on October 12, 2017. The purpose of EO 13813 was to increase competition in the ACA by improving and developing alternative coverage arrangements such as associated health plans and short-term limited-duration insurance plans. The final rule for each plan was passed in June 2018 and August 2018, respectively. These plans are appealing to healthy consumers because of their premiums, but they typically do not have coverages compliant with the ACA and are medically underwritten. For example, they often exclude coverage of essential health benefits such as maternity care, prescription drugs, or mental health care needed to meet the ACA's requirement to maintain coverage (NAIC, 2020). However, because the penalty for being uninsured has been decreased to $0, these plans remain attractive for healthy individuals. State laws to regulate them varied widely. For instance, Massachusetts, New Jersey, and New York did not permit short-term plans that are underwritten. In other 47 states and D.C., insurers could refuse to issue or renew a short-term policy based on a consumer's health status. Therefore, the impact of these plans on coverage rates would depend on the extent to which states strictly regulate them.

II. Literature Review

Despite the controversy about the individual mandate and its effect on coverage rates, there have been few studies investigating the direct evidence of how the individual mandate has affected insurance coverage. This is largely due to the challenge of isolating the mandate's effect arising from the mandate being implemented at the same time as the ACA's other major coverage provisions.

The best evidence comes from Massachusetts, which had a health reform that included an individual mandate in 2006. Hackmann, Kolstad, and Kowalski developed a model of selection that incorporates an individual mandate. They estimated the slopes of the average cost and demand curves using insurer enrollment, premium, and health expenditure information from regulatory filings of insurance companies combined with the enrollment information with coverage information from the National Health Interview Survey and found clear effects of the individual mandate in the non-group market in Massachusetts. The study confirmed that adverse selection abated after individuals began to enroll in response to the individual mandate (Hackmann, Kolstad, Kowalski 2015). While they focused on the non-group market, I take a broader approach by categorizing individuals into insured or uninsured regardless of the kind of insurance and thus analyze all health insurance markets.

In addition to the lack of literature, there are some disagreements within it. Frean, Gruber, and Sommers showed that the individual mandate had a little, inconsistent impact on coverage rates for non-elderly individuals regardless of income in 2014 and 2015. Using 2012–2015 ACS data, they conducted a DD that exploits variation based on geography and income in the ACA policy levers to identify changes in coverage over time, adjusting for time, geography, and income. The coefficient of interest measured the impact of the mandate in 2014 and 2015 separately since the policy evolved over time, and the dependent variable was the percent of each health insurance unit without insurance at the time of the survey. The coefficients in 2014 and 2015 were negligible in magnitude and wrong-signed (i.e., higher mandate led to more uninsured) (Frean et al. 2017). While I analyze the effect of the individual mandate by using the DD model that exploits the variation by state-level mandates, they used a triple difference approach and reached an opposite conclusion to my hypothesis. The authors' model explained 60% of the coverage gains but with my identification strategy that examines only high-income groups and has fewer policy changes happening concurrently, I can get a more direct effect of the mandate on coverage rates. Lurie, Sacks, and Heim (2021) estimated the effect of the individual mandate on insurance coverage based on tax returns. Their regression discontinuity and regression kink designs exploited two nonlinearities: (1) people are exempt from the penalty if their income is below 138 percent of the FPL and they live in a state that did not expand Medicaid, and (2) the penalty amount is a kinked function of income. They found that the actual penalty paid per uninsured month is less than half the statutory amount. Additionally, they observed visually clear and statistically significant responses to both extensive margin exposure to the mandate and marginal increases in the mandate penalty. Their estimates implied fairly small quantitative responses to the mandate.

On the other hand, there are other studies with different methodologies, but all indicate that there is a large effect of the mandate on coverage rates. A survey conducted with individual-market enrollees in California in 2017 reported that 19 percent of them would not have purchased insurance in the absence of a penalty (Fung et al. 2019). As the survey was fielded before the elimination of the mandate penalty, it only provides prediction but no direct evidence for the effect of the mandate. A study by Jacobs utilized a DD design to present a sizable effect of the mandate. Although both the individual mandate and Marketplaces offering menus of community-rated and guaranteed issue plans being introduced in 2014 complicated the effort to separately identify their effects, he utilized the fact that some states implemented non-group market reforms before 2014. Using the ACS from 2012 through 2016, he exploited this state-level variation in the rules governing premium setting and the size of the penalty for non-compliance with the mandate over time, by family size, and by income level. Similar to my paper, Jacobs focused on the non-elderly adults with incomes above 400 percent of the FPL because they are not affected by the expansion of Medicaid or subsidies for Marketplace coverage. He found that the individual mandate penalties were associated with 7 to 12 percentage points of the 13-percentage-point increase in coverage in the non-group market for higher-income adults (Jacobs 2018). By similarly examining non-elderly individuals with incomes above 400 percent of FPL and exploiting state-level variation but with a different policy change, my paper adds value by looking at the effect of individual mandate with the most recent data and policy. Another way studies have tried to illustrate the effect of health insurance mandates is by making projections. The Congressional Budget Office (CBO) made projections for the 2019 to 2028 period using its health insurance simulation model HISIM2, a microsimulation model that incorporates models that included post-ACA evidence. Its model included non-elderly people as in my paper, but individuals were from all income groups. CBO projected that the repeal of the federal mandate will result in 30 million uninsured in 2019, which is a 1 million increase from 2018 and 2 million from 2017. Furthermore, the number of uninsured will rise to 35 million in 2029 according to its report (CBO 2019). As opposed to examining the short-run effect of the mandate in my analysis, CBO provides a long-run view of the mandate's effect on coverage rates.

There has also been a study that implemented an information treatment randomized control trial using the mandate as a tool to design it. Authors studied how informational letters sent by IRS to households that paid a tax penalty for not having health insurance coverage under the ACA led to a small increase in coverage and reduced mortality among middle-aged adults during the two years. Those in the treatment group were 1.1 percentage points more likely to enroll in coverage than those in the control group (Goldin et al. 2021). The magnitude of the effect is bigger than my study due to a larger sample. While the authors sent letters to 3.9 million households, my sample consists of about 1.2 million individuals per year. Therefore, the authors were able to detect the small, statistically detectable effect even though they implemented an information treatment that typically does not have a big effect. Additionally, the authors are trying to nudge people and inform them into actually taking action in signing up while my paper is about simply observing how people react to the new state requirement.

For the literature on racial/ethnic insurance coverage disparities, some papers analyze the impact of healthcare policies such as ACA, Medicaid expansions, and individual mandate on coverage rates by race/ethnicity. Depending on the sample, the differential effects across racial/ethnic groups varied. For instance, coverage disparities decreased, with a bigger decrease in uninsured among Hispanics and Blacks relative to Whites or between Non-Whites and Non-Hispanic Whites more broadly after the ACA provisions and Medicaid expansion when focusing on non-elderly adults from all income levels (Buchmueller et al. 2016; Courtemanche et al. 2019a; Courtemanche et al. 2019b; Sommers 2015). In contrast, the coverage gap was further enlarged between Non-Hispanic Whites and Hispanics in expansion states after the Medicaid expansion when examining low-income non-elderly adults (Angier et al. 2017; Yue et al. 2018). Another study compared observations from when the mandate penalty was in effect (2016-2018) and the year it was eliminated (2019) and observed that the Latino population experienced the largest increase in the probabilities of being uninsured compared to non-Latino Black and White populations (Ortega et al. 2022). However, no paper analyzes specifically the impact of state mandate by race/ethnicity among high-income individuals. The closest is the survey conducted with individual-market enrollees in California in 2017 in which it further analyzed its results based on race and income, among others. The percentages of enrollees who would forgo insurance in the absence of penalty were higher among those with lower income and education and Hispanics, relative to the comparison groups (Fung et al. 2019).

There has been no study that analyzes the effect of state individual mandates that were implemented starting in 2019, mainly due to a lack of recent data. Excluding the studies on Massachusetts health reform, no study exploits the state-level difference in the mandate. Now, with Washington D.C. and New Jersey enacting their own state individual mandate, I can exploit such difference. My paper is one of the first attempts to evaluate the direct effect of the mandate on coverage rates, contributing to the continuing but still unclear debate on the impact of the individual mandate. Furthermore, my paper adds to the lacking literature on the effect of the individual mandate on coverage rates by race/ethnicity among high-income individuals.

III. Data

The ACS provides repeated cross-section data on health insurance coverage, demographic, and socioeconomic identifiers. The US Census Bureau annually takes a nationally representative 3-million-person sample and sends self-response mail-out/mail-back questionnaires with internet response options, then conducts follow-ups with interviewers.

I include data from 2014 to 2019. Although 2019 is not the last year of ACS data currently available, I do not include 2020 data because the ACS 2020 1-year file uses experimental weights to account for the effects of the COVID-19 pandemic on the ACS 2020 data products. Therefore, the Census Bureau advises against comparing the data to other ACS sample years. There are also data quality issues such as lower coverage rates for underrepresented populations (e.g., Non-Hispanic Black and Hispanic respondents) (Rothbaum et al. 2021). As the paper analyzes racial/ethnic disparities as one of the main focuses, such issues can bias the results. 47 contiguous states and Washington D.C. (excluding Massachusetts because a 2006 health reform law included an individual mandate) are analyzed.[1] I focus on income above 400 percent of the FPL as individuals are not eligible for the ACA's subsidies. This makes it easier to isolate any effects of the individual mandate. I drop all individuals 65 and above because the individual mandate does not apply to them. I then stratify the sample by race/ethnicity. The total sample includes 7,269,024 individuals.

The main outcome variable of interest is health insurance coverage. Individuals are defined as insured if they are covered by at least one of the following types: (1) employment-based coverage, (2) privately purchased insurance, (3) Medicaid, Medicare, or any other governmental

[1] I restrict the states to contiguous states and D.C. because they all use the same Federal Poverty Guidelines while Alaska and Hawaii each has their own Federal Poverty Guideline. Alaska and Hawaii are only 0.68% of the data.

Table 1. Summary Statistics for Main and Control Variables

Variable	N	Mean	Std. Dev.	Min	Max
Health Insurance Coverage	7269024	.939	.24	0	1
Year	7269024	2016.58	1.707	2014	2019
State	7269024	27.78	16.309	1	56
Gender	7269024	.496	.5	0	1
Marital status	7269024	3.438	2.368	1	6
Age	7269024	37.109	18.034	0	64
Citizen	7269024	.297	.803	0	3
White	7269024	.815	.389	0	1
Black	7269024	.075	.263	0	1
Hispanic	7269024	.122	.327	0	1
Other race	7269024	.032	.176	0	1
Race/ethnicity	7269024	1.553	.985	1	4
FPL	7269024	897.316	652.296	400	26632.996
Education	7269024	2.843	1.348	1	5
Unemployment rate	7269024	4.699	1.115	2.3	8.2

insurance, (4) TRICARE or other military care, or (5) Veterans Administration-provided insurance. Individuals covered under Indian Health Service (IHS) (excluding IHS because its policies are not always comprehensive) or not covered by any of the five types of insurance are classified as uninsured. For control variables, I use demographic data including gender, age, marital status, race, citizenship status, and educational attainment. Additionally, I use data from the BLS for yearly unemployment rates for each state. Unemployment rates are used to control for differences in economic conditions across states. Table 1 provides the summary statistics for the main and control variables.[2]

IV. Methods

A. Differences-in-Differences

My analysis is a difference-in-differences (DD) regression model examining the impact of the state individual mandate on health care coverage among high-income, non-elderly individuals aged under 65 and with family income above 400 percent FPL. The natural variation comes from New Jersey and Washington D.C. implementing a state mandate on January 1, 2019, while the other 46 states implementing none after the federal individual mandate repeal in 2019. All models are first run with both New Jersey and Washington D.C. included as treated states (pooled model). Since I implement synthetic control for each treatment state separately later, I also separately run all models again with first including New Jersey only and second Washington D.C. only as a treated state.

$$\text{Model 1: } Coverage_{ist} = \beta_0 + \beta_1 Mandate_s + \beta_2 Post_t + \beta_3 Mandate_s \times Post_t$$
$$+ \beta_x \mathbf{X}_{ist} + \delta_s + \tau_t + \varepsilon_{st}$$

Model 1 is a pre-post DD regression with individual-level controls. $Coverage_{ist}$ is a 0/1 indicator for coverage status for individual i in state s in year t. $Mandate_s$ is a 0/1 indicator for states that implemented a state individual mandate (treatment group) versus those that did not (control group). $Post_t$ is a 0/1 indicator for the post-treatment period (2019). $\mathbf{X}_{ist}$ is a set of individual-level controls, which includes gender, marital status, age, citizenship status, and educational attainment. δ_s denote state fixed effects. Because the executive order that improved

[2] See the appendix for summary statistics of each racial/ethnic group.

alternative coverage arrangements were regulated differently across states and ACS does not distinguish whether the individuals were covered under alternative coverage arrangements that would not count as insured under ACA, state fixed effect is used to further account for any underlying state-level differences. τ_t is year fixed effects. ε_{st} is the error term. Standard errors are clustered at the state level. The coefficient of interest is β_3, which indicates the DD estimate (comparing pre-post coverage differences in states with a mandate and states without a mandate) and captures the treatment effect of state individual mandate on health insurance coverage. The coefficient estimate has a causal interpretation under the assumption that changes in health insurance coverage after 2019 would have been the same in states with a mandate and states without a mandate but for the state mandate, conditional on the other covariates.

$$\text{Model 2: Coverage}_{ist} = \beta_0 + \beta_1 \text{ Mandate}_s + \beta_2 \text{ Post}_t + \beta_3 \text{ Mandate}_s \text{ x Post}_t$$
$$+ \beta_x \mathbf{X}_{ist} + \delta_s + \tau_t + \text{Unemp}_{st} + \varepsilon_{st}$$

Model 2 is a pre-post DD regression identical to Model 1 but adds an unemployment rate. Unemp_{st} is a state-year-specific unemployment rate, which is used to control for state-level differences in unemployment's effect on health insurance coverage.

B. Event-study

$$\text{Model 1: Coverage}_{ist} = \beta_0 + \beta_1 \text{ Mandate}_s + \textstyle\sum_{k=2014}^{2019} \beta_2 \mathbf{1}\{\mathrm{K_{it}} = \mathrm{k}\}$$
$$+ \textstyle\sum_{k=2014}^{2019} \beta_3 \text{ Mandate}_s \text{ x } \mathbf{1}\{\mathrm{K_{it}} = \mathrm{k}\} + \beta_x \mathbf{X}_{ist} + \delta_s + \varepsilon_{st}$$

$$\text{Model 2: Coverage}_{ist} = \beta_0 + \beta_1 \text{ Mandate}_s + \textstyle\sum_{k=2014}^{2019} \beta_2 \mathbf{1}\{\mathrm{K_{it}} = \mathrm{k}\}$$
$$+ \textstyle\sum_{k=2014}^{2019} \beta_3 \text{ Mandate}_s \text{ x } \mathbf{1}\{\mathrm{K_{it}} = \mathrm{k}\} + \beta_x \mathbf{X}_{ist} + \delta_s + \text{Unemp}_{st} + \varepsilon_{st}$$

To statistically test for parallel trend, I run an event-study regression for each model. All variables are defined as before. $\mathbf{1}\{\mathrm{K_{it}} = \mathrm{k}\}$ is a 0/1 indicator for each year with 2018 as the omitted year. Therefore, the predicted counterfactual in each period is relative to 2018. For instance, β_3

when $\mathrm{K}_{\mathrm{it}} = 2014$ would be the magnitude of the coverage rate difference between treatment and the control group of 2014 minus the magnitude of the coverage rate difference between treatment and the control group of 2018. The coefficient of interest β_3 is plotted on the graph for each year. As done in the DD regression, all models are first run with both New Jersey and Washington D.C. included as treated states (pooled model) and separately run again with first including New Jersey only and second Washington D.C. only as a treated state.

C. Synthetic Control

To address the concern for parallel-trend and different health insurance coverage trends in all states, I implement synthetic control for New Jersey and Washington D.C. separately. I rely on the synthetic control method proposed in Abadie and Gardeazabal (2003), Abadie et al. (2010), and Wiltshire (2021). The synthetic control chooses a weighted average of control states to find the best synthetic New Jersey and synthetic Washington D.C. groups for the outcome variable and other observed characteristics before the state mandate is implemented. To test for statistical significance of the results, rmpse-ranked p-values from in-space treatment permutations are calculated for both New Jersey and Washington D.C.. The main and control variables are aggregated at the state and year level, following Jones and Marinescu's methodology which also uses microdata from the CPS (Jones and Marinescu 2018). For New Jersey, Washington D.C. is excluded from being included as synthetic New Jersey. Similarly, New Jersey is excluded from being included as synthetic Washington D.C..

D. Race Heterogeneity Analysis

To examine racial/ethnic disparities in health insurance coverage, I conduct a heterogeneity analysis using the same DD specifications above but subsampling the individuals by different racial/ethnic groups. Individuals are categorized among four groups: Non-Hispanic White, Non-

Hispanic Black, Hispanic, and Non-Hispanic other race. Non-Hispanic other race includes American Indian or Alaska Native, Chinese, Japanese, Other Asian or Pacific Islander, and Other race. The different groups are chosen based on previous papers that analyze coverage disparities by race/ethnicity (Wehby and Lyu 2018; Menon et al. 2021).

E. Racial Gap Analysis

To further investigate the effect of the individual mandate on racial/ethnic disparities, I implement the empirical methodology by Derenoncourt and Montialoux (2021). First, I analyze the economy-wide coverage gaps (i.e., the difference in mean health insurance coverage rate between two racial/ethnic groups) each year between Non-Hispanic Black and Non-Hispanic White, and Hispanic and Non-Hispanic White individuals. Then, I run a regression model to investigate the effect of the state mandate in the evolution of the adjusted (i.e., controlling for observable characteristics) racial coverage gap. The equation is estimated for individuals in the treated and control states separately:

$$\text{Black-White gap: } Coverage_{ist} = \beta_0 + \beta_1\, NHBlack_i + \sum_k \beta_k\, NHBlack_i \text{ x } \delta_{t+k}$$

$$+ \beta_x\, \mathbf{X}_{ist} + \delta_s + \tau_t + \varepsilon_{st}$$

$$\text{Hispanic-White gap: } Coverage_{ist} = \beta_0 + \beta_1\, Hispanic_i + \sum_k \beta_k\, Hispanic_i \text{ x } \delta_{t+k}$$

$$+ \beta_x\, \mathbf{X}_{ist} + \delta_s + \tau_t + \varepsilon_{st},$$

where $NHBlack_i$ is a 0/1 indicator variable for being a Non-Hispanic Black individual and $Hispanic_i$ is a 0/1 indicator variable for being a Hispanic individual. δ_{t+k} is a year variable. $\mathbf{X}_{ist}$ is a set of individual-level controls as before. δ_s is the state fixed effect, and τ_t is the year fixed effect. ε_{st} is the error term, again clustered at the state level.

V. Results and Discussion

A. The Impact of State Individual Mandate

Table 2 shows the main results for Model 1 and Model 2. Column 1 in this table displays the DD estimate for health insurance coverage rate without the state unemployment rate included as a control. Although the estimator of interest is *Mandate x Post*, the intervention effect, I start by describing what the other coefficients imply. Over time, the insurance rate increases by 1.09 percentage points. States with a mandate have a higher coverage rate overall. Male individuals have 1.4 percentage points higher coverage than females. Those who are married are less likely to be insured. An additional year of age is associated with a 0.146 percentage points decrease in coverage rates, all else equal. U.S. citizens are less likely to be insured while higher education level is associated with a higher rate of coverage. Column 2 which adds unemployment as control shows that a 1 percent increase in the unemployment rate is associated with a 0.393 percentage point decrease in coverage, but it is statistically insignificant.

The main result indicates that the state individual mandate increased health insurance coverage for the high-income non-elderly individuals in treatment states by 0.502 percentage points. The effect is statistically significant at the 1 percent level. After controlling for the state unemployment rate, the main result shows a smaller and statistically insignificant 0.309 percentage point increase in health insurance coverage rate.

The result was expected to be positive as preserving the mandate keeps the health insurance high relative to the states without it where they experience decreases in coverage. However, the effect is smaller compared to Jacobs that similarly examined the effect of the individual mandate on high-income individuals (2018). This may be because there is only one year of post-treatment data, and thus the result shows the short-run effect. Overall, these findings support my hypothesis that the state individual mandate will increase the health insurance coverage rate among high-income, non-elderly individuals. In addition, based on the sample health insurance coverage rate of 93.9 percent, there is a 6.1 percentage point gap for the mandate to potentially fill. That means that a 0.502 percentage point increase is an 8.2 percent increase in coverage for Model 1. 0.309 percentage point increase is a 5.6 percent effect for Model 2, but statistically insignificant.

Table 2. The Effect of State Mandate on Insurance Coverage (Pooled)

Variable	(1) Model 1	(2) Model 2
Post	0.0109***	0.00111
	(0.00275)	(0.00550)
Mandate	0.0217***	0.0214***
	(0.000783)	(0.000879)
Mandate x Post	0.00502***	0.00309
	(0.00124)	(0.00186)
Gender	0.0140***	0.0140***
	(0.000731)	(0.000731)
Marital status	-0.0148***	-0.0148***
	(0.000748)	(0.000748)
Age	-0.00146***	-0.00146***
	(9.38e-05)	(9.38e-05)
Citizen	-0.0391***	-0.0391***
	(0.00280)	(0.00280)
Education	0.0152***	0.0152***
	(0.00146)	(0.00146)
Unemp		-0.00393
		(0.00251)
Constant	0.986***	1.011***
	(0.00465)	(0.0143)
Observations	7,266,452	7,266,452
R-squared	0.044	0.044
State FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

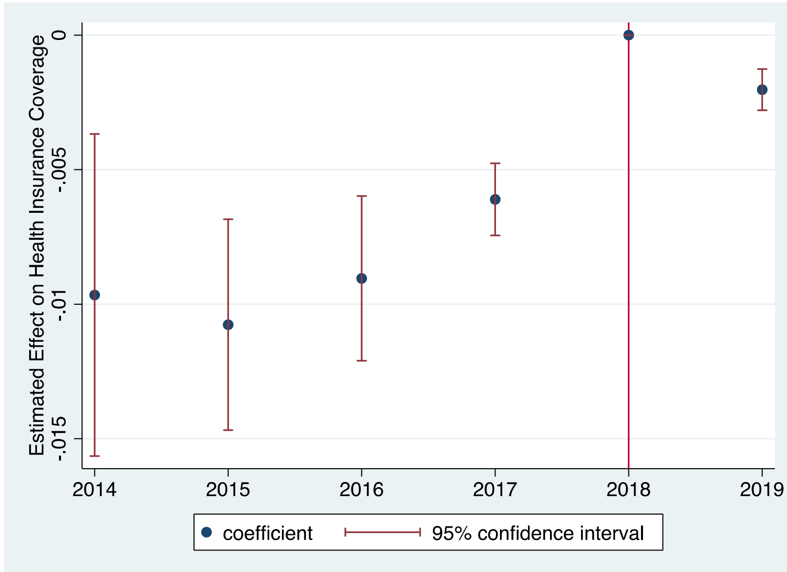

Figure 1. Event-study (Model 1, pooled)

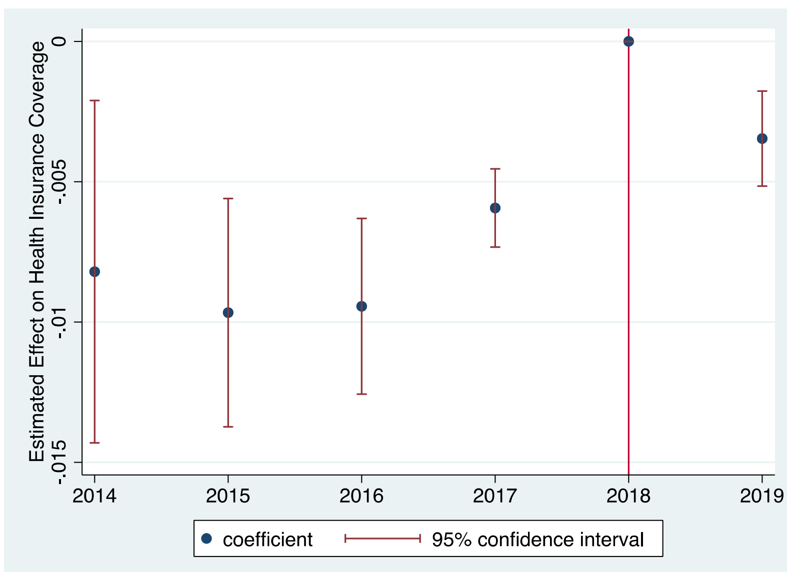

Figure 2. Event-study (Model 2, pooled)

Both event-study graphs for Model 1 and Model 2 display a slightly increasing trend before the state mandate with a decrease in the coefficient after the state mandate (Figure 1 and Figure 2). Without a flat pre-trend, it is hard to explain what is driving the result. However, it is important to point out that the pre-trend is moving in a different direction than the post-policy effect that I am finding. It would be more of a concern if I had the pre-trend and the coefficient continued to increase after the mandate. In that case, the effect would have been dismissed as an extension of the existing pre-trends. But it is still questionable why the coefficient goes up starting from 2018, which is still a pre-policy year. Additionally, the coefficient in 2019 is decreasing, which is going in the wrong direction. A hypothesis for the pre-trend is that individuals may not be aware of the state individual mandate or the repeal at the federal level (Kirzinger et al. 2018). It may take time for information to disseminate both in states with the individual mandate and those without. People may be reacting before the state mandate actually gets implemented because they are not fully informed.

It is still important to acknowledge and address the concern with pre-trend. The time path of the event-study raises a question about whether it is truly the mandate that causes an increase in coverage rates. Although the graph shows how a DD leads to a positive estimate, the event-study shows the coefficient turns negative in 2019. Therefore, I implement synthetic control for New Jersey and Washington D.C. to find a better control group on a statistical, data-driven basis. But before advancing to the synthetic control, I first look at the DD and event-study one treated state at a time since I will have to do so for synthetic control.

New Jersey's Model 1 and Model 2 results for DD and event-study are both consistent with the result in the pooled models but smaller in magnitude. Model 1 suggests that New Jersey's mandate increased health insurance coverage by 0.487 percentage points (Column 1, Table 3). The effect is statistically significant at the 1% level. Adding unemployment, the result indicates a 0.275 percentage points increase in coverage, but the effect is not statistically significant. The event-study graphs for both Model 1 and Model 2 are also similar to the pooled model, with a concern for parallel trend (Figure 3 and Figure 4).

Table 3. The Effect of State Mandate on Insurance Coverage (New Jersey)

Variable	(1) Model 1	(2) Model 2
Mandate x Post	0.00487***	0.00275
	(0.00124)	(0.00191)
Unemp		-0.00396
		(0.00251)
Observations	7,245,193	7,245,193
R-squared	0.044	0.044
State FE	Yes	Yes
Year FE	Yes	Yes
Individual controls	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

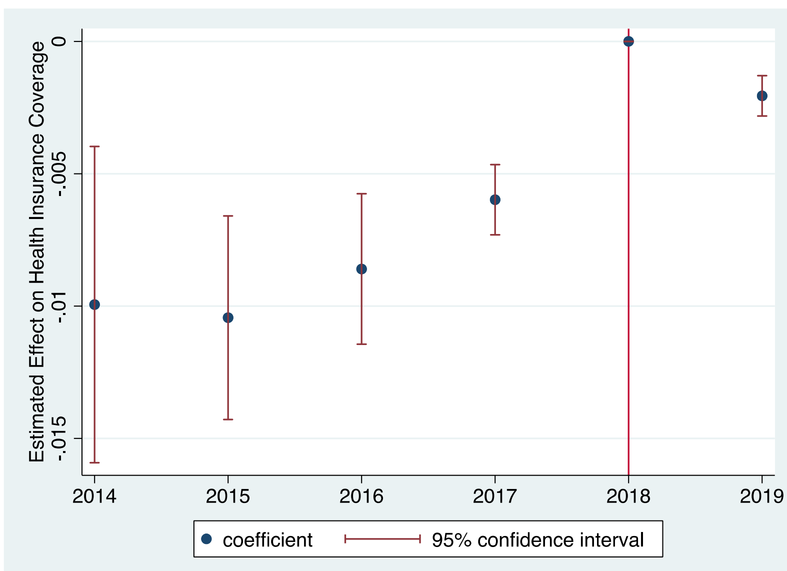

Figure 3. Event-study (Model 1, New Jersey)

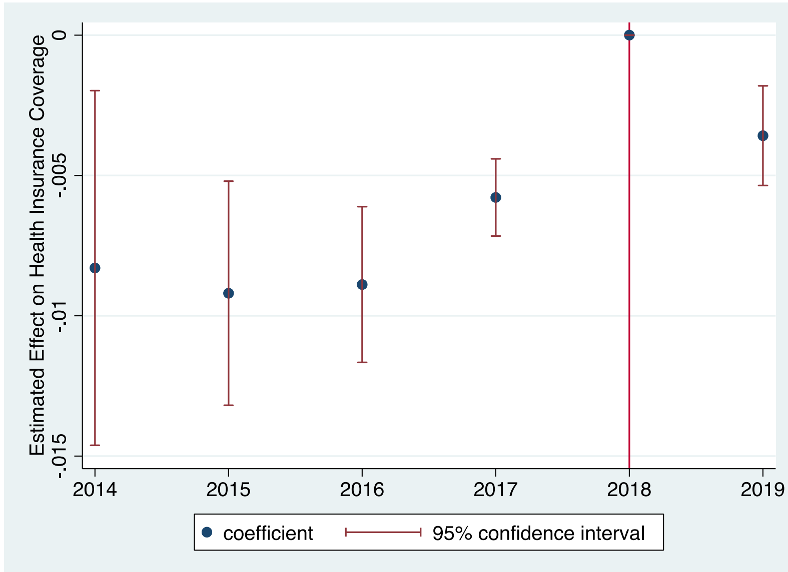

Figure 4. Event-study (Model 2, New Jersey)

Washington D.C.'s results for DD are again qualitatively consistent, but bigger in magnitude compared to the pooled model and statistically significant in both models. The effect of the state mandate in Washington D.C. is 0.688 percentage points increase in coverage, and it is statistically significant at the 1% level (Column 1, Table 4). After including the state unemployment rate, health insurance coverage increases by 0.726 percentage points, statistically significant at the 1% level (Column 2, Table 4). The event-study graphs for both Model 1 and

Table 4. The Effect of State Mandate on Insurance Coverage (Washington D.C.)

Variable	(1) Model 1	(2) Model 2
Mandate x Post	0.00688***	0.00726***
	(0.00100)	(0.000909)
Unemp		-0.00386
		(0.00259)
Observations	6,990,035	6,990,035
R-squared	0.043	0.043
State FE	Yes	Yes
Year FE	Yes	Yes
Individual controls	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Model 2 again raise a concern for parallel trend assumption (Figure 5 and Figure 6). The coefficient before the state mandate first decreases, then increases until 2018. Then, the coefficient decreases again after the mandate in 2019.

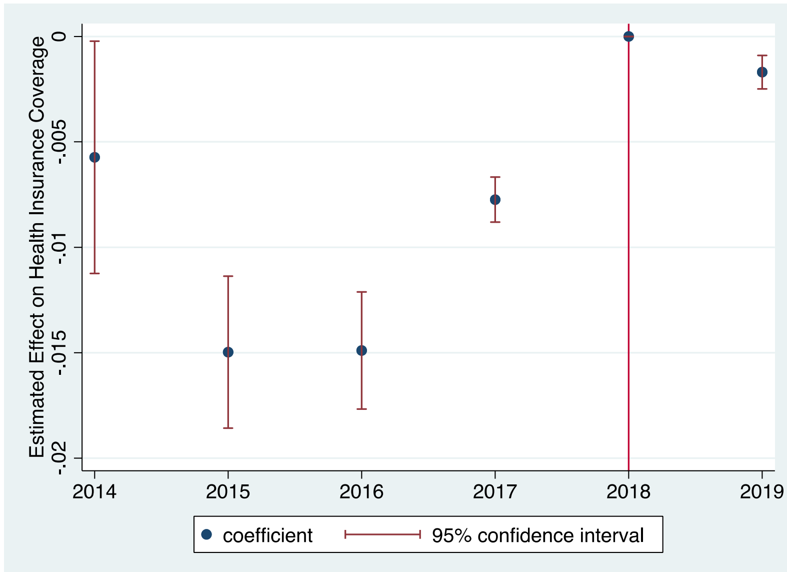

Figure 5. Event-study (Model 1, Washington D.C.)

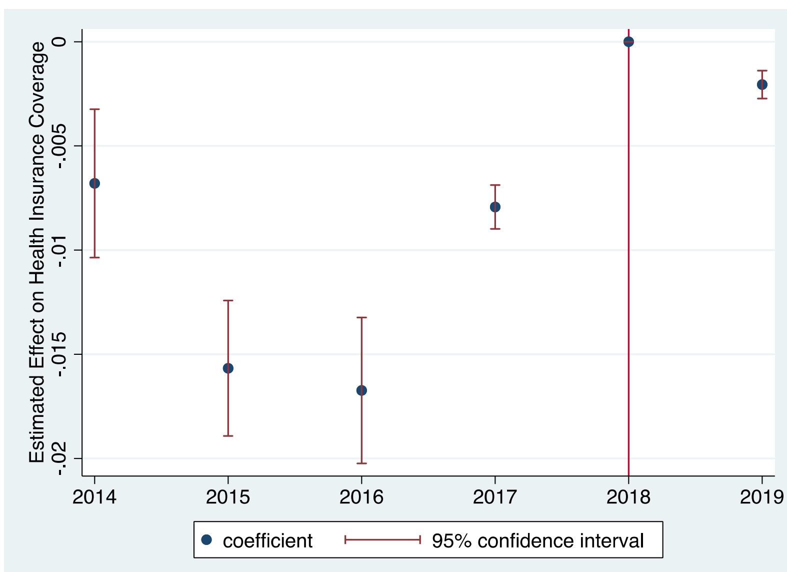

Figure 6. Event-study (Model 2, Washington D.C.)

In addition to the pre-trend concern for the pooled, New Jersey, and Washington D.C. models, different time path of health insurance coverage in each state raises a need to implement synthetic control (Figure 7). Using synthetic control, I am able to use a data-driven method to find the best counterfactual for New Jersey and Washington D.C. instead of pooling all states excluding the two as a control group.

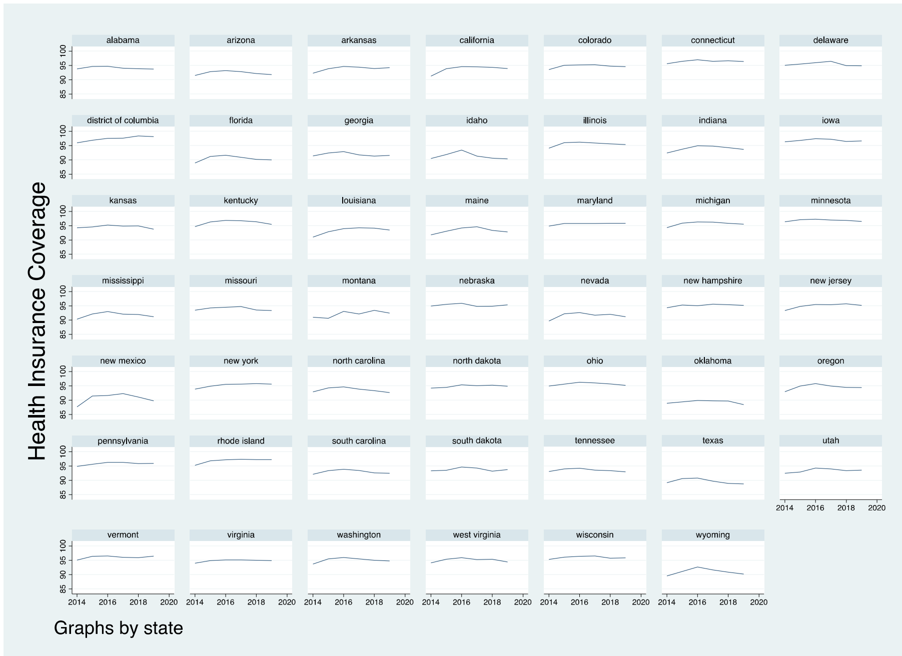

Figure 7. Time series of health insurance coverage for all states

Synthetic New Jersey consists of California, New York, and Rhode Island with the weights being 21.3 percent, 73.9 percent, and 4.8 percent, respectively (Table 5). It is similar to New Jersey based on individual characteristics such as gender, marital status, age, citizen, and education along with the outcome variable in pre-policy years (Table 6). Figure 8 displays a reasonable counterfactual for New Jersey but suggests a negative effect of the mandate, which is the opposite of my hypothesis. While synthetic New Jersey's health insurance coverage decreases, New Jersey's decreases even more. But the main effect is a small 0.225 percentage points decrease. Additionally, the result is statistically insignificant, with the p-value being about 23.4 percent (Table 7). There could potentially be policies other than the mandate in California, New York, or Rhode Island that I am not capturing. Because I am relying on only 1 post-year data, they can make a difference in the result.

Table 5. Synthetic New Jersey Unit Weights

State	Unit Weight
California	0.213
New York	0.739
Rhode Island	0.048

Table 6. Predictor Balance (New Jersey)

Variable	Treated	Synthetic
Gender	0.5013521	0.50041
Marital Status	3.528725	3.66131
Age	35.93999	36.31134
Citizen	0.4519813	0.4771463
Education	2.883009	2.896369
Health Insurance Coverage 2018	95.65263	95.54308
Health Insurance Coverage 2014	93.31886	93.34248
Health Insurance Coverage 2016	95.46323	95.47214

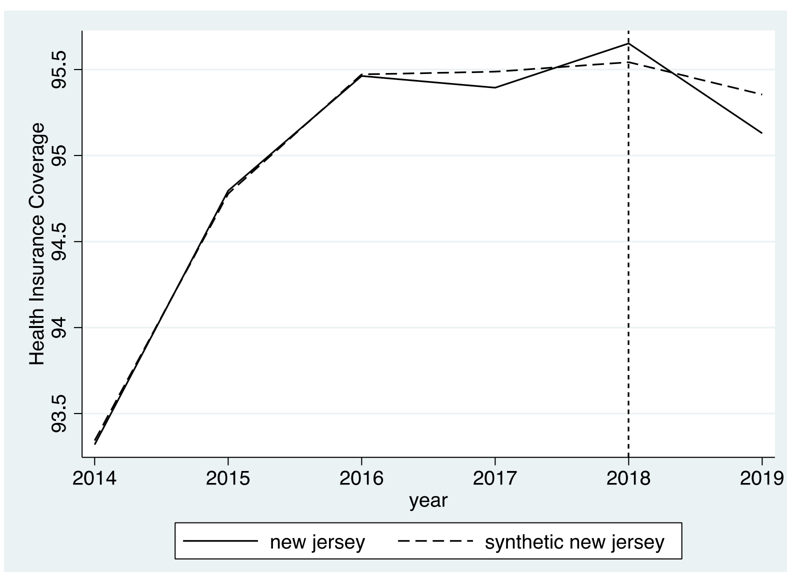

Figure 8. Health Insurance Coverage: New Jersey vs. Synthetic New Jersey

Table 7. Treated Unit Results (New Jersey)

State	Year	Gap	rmspe	rmspe~k	p	N
New Jersey	2014	-0.0236287	.	.	.	47
	2015	0.0168223	.	.	.	47
	2016	-0.0089028	.	.	.	47
	2017	-0.092832	.	.	.	47
	2018	0.1095446	.	.	.	47
	2019	-0.2250792	11.76056	11	0.2340426	47

For synthetic Washington D.C., Minnesota is weighted by 32.3 percent and Rhode Island has a unit weight of 67.7 percent (Table 8). It is harder to find the best synthetic group for Washington D.C.. Excluding gender, other observable characteristics such as marital status, age, citizen, and education are not very similar. The outcome variables in pre-policy years are fairly similar but less so compared to synthetic New Jersey and New Jersey (Table 9). Figure 9 displays a synthetic Washington D.C. that trends differently from Washington D.C. before the mandate. The result suggests a small 1.15 percentage point increase in coverage due to the mandate, which is consistent with the expectation. But it is again statistically insignificant, with the p-value being about 48.94 percent (Table 10). Although both results of synthetic control for New Jersey and Washington D.C. are not statistically significant, it is qualitatively consistent with the story of the DD and event-study because the effect of the mandate is not very big in magnitude.

Table 8. Synthetic Washington D.C. Unit Weights

State	Unit Weight
Minnesota	0.323
Rhode Island	0.677

Table 9. Predictor Balance (Washington D.C.)

Variable	Treated	Synthetic
Gender	0.5110746	0.4959511
Marital Status	4.213988	3.45358
Age	34.1115	37.36493
Citizen	0.3457517	0.1938959
Education	3.606017	2.857234
Health Insurance Coverage 2018	98.38289	97.12191
Health Insurance Coverage 2014	95.96609	95.47907
Health Insurance Coverage 2016	97.54999	97.1814

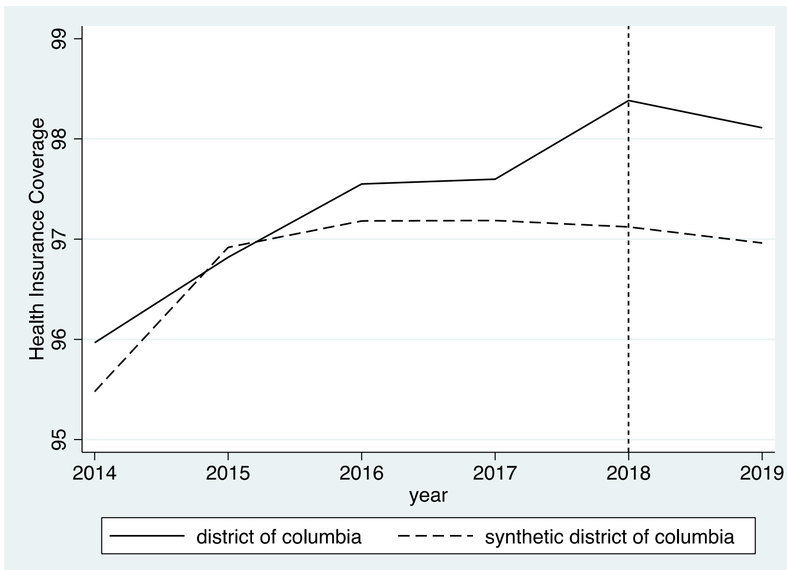

Figure 9. Health Insurance Coverage: Washington D.C. vs. Synthetic Washington D.C.

Table 10. Treated Unit Results (Washington D.C.)

State	Year	Gap	rmspe	rmspe~k	p	N
District of Columbia	2014	0.4870206	.	.	.	47
	2015	-0.0989796	.	.	.	47
	2016	0.3685913	.	.	.	47
	2017	0.4117537	.	.	.	47
	2018	1.260978	.	.	.	47
	2019	1.150572	3.089491	23	0.4893617	47

B. Race Heterogeneity Analysis

To get a general overview of health insurance coverage for different racial/ethnic groups, I plot a yearly time series graph at the national level. Mean coverage rate for each racial group progresses fairly similarly with an increase from 2014 to 2016, then a general decline afterwards (Figure 10). Non-Hispanic White individuals have the highest health insurance coverage rate, followed by Non-Hispanic other race, Non-Hispanic Black, and Hispanic individuals.

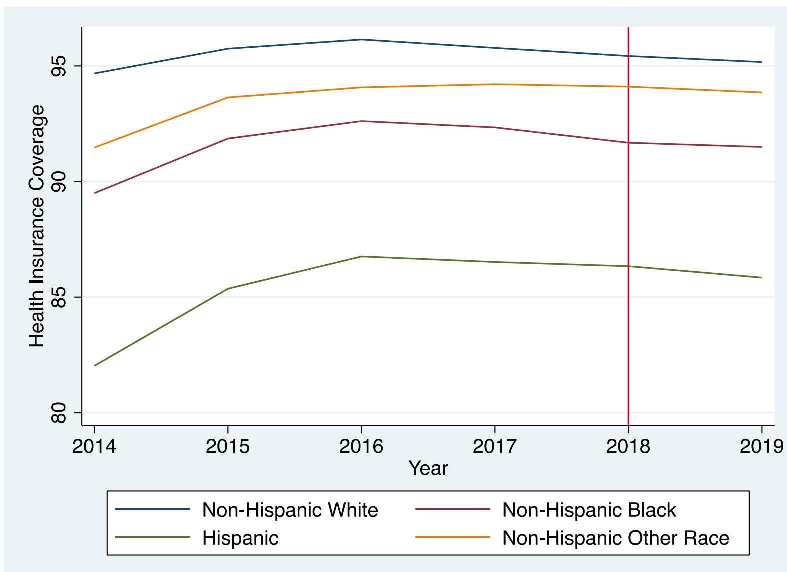

Figure 10. Health Insurance Coverage by Race

Using all models, I investigate whether there are disparities in health insurance coverage among different racial/ethnic groups. Table 11 shows the results for the four racial/ethnic groups using the main model. As before, the estimator of interest is *Mandate x Post*. For Non-Hispanic Whites, coverage rates after mandate increased by 0.416 percentage points, statistically significant at the 1 percent level. There is a statistically significant 0.449 percentage point increase among Non-Hispanic Black individuals. The largest, statistically significant effect is seen among Hispanics; health insurance coverage increased by 0.671 percentage points. The effect is the smallest for Non-Hispanic other race individuals, with a 0.235 percentage point increase, statistically significant at the 1 percent level.

Table 11. The Effect of State Mandate on Insurance Coverage by Race/Ethnicity (Model 1)

Variable	(1) Non-Hispanic White	(2) Non-Hispanic Black	(3) Hispanic	(4) Non-Hispanic Other Race
Mandate x Post	0.00416***	0.00449*	0.00671*	0.00235***
	(0.00106)	(0.00230)	(0.00375)	(0.000783)
Observations	5,288,486	524,745	866,736	586,485
R-squared	0.021	0.032	0.103	0.045
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12 similarly shows the main results for the four racial/ethnic groups using Model 2. For Non-Hispanic Whites, coverage rates increased by 0.331 percentage points, but are now statistically significant at the 5 percent level. The largest, statistically significant effect is seen among Non-Hispanic Blacks with health insurance coverage increasing by 0.461 percentage points. There is a small 0.183 percentage point increase among Hispanic individuals, and it is statistically insignificant. The coefficients for other racial/ethnic groups do not change as much from Model 1 but do so for Hispanics. Their *Unemp* coefficient is statistically significant and negative, which implies that when the unemployment rate increases, their coverage rate decreases. This could mean that states that are imposing the mandate are correlated with the economic cycle, and Hispanics are more cyclically sensitive to the cycle, which could be related to the jobs they hold. Coverage rates for Non-Hispanic other race individuals increased by 0.139 percentage points, but it is statistically insignificant.

Table 12. The Effect of State Mandate on Insurance Coverage by Race/Ethnicity (Model 2)

Variable	(1) Non-Hispanic White	(2) Non-Hispanic Black	(3) Hispanic	(4) Non-Hispanic Other Race
Mandate x Post	0.00331**	0.00461**	0.00183	0.00139
	(0.00138)	(0.00209)	(0.00354)	(0.00138)
Unemp	-0.00160	0.000415	-0.0119**	-0.00226
	(0.00159)	(0.00360)	(0.00511)	(0.00234)
Observations	5,288,486	524,745	866,736	586,485
R-squared	0.021	0.032	0.103	0.045
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For Model 1, Hispanics were most likely to become insured after the state individual mandate, followed by Non-Hispanic Blacks, Non-Hispanic Whites, and other Non-Hispanic race individuals. This aligns with my hypothesis that the state individual mandate will reduce the racial/ethnic disparities, with a bigger increase in Hispanics and Non-Hispanic Blacks than Non-Hispanic Whites. The result of Model 2 is generally in line with my hypothesis as well. Non-Hispanic Blacks experienced a larger increase in coverage than Non-Hispanic Whites, but Hispanics experienced a smaller increase. However, the result for Hispanics is statistically insignificant while the results for Non-Hispanic Blacks and Non-Hispanic Whites are statistically significant. In summary, the results that align with my hypothesis are statistically significant whereas those that do not are statistically insignificant. These results were partly expected as past literature examining the effect of healthcare policies such as ACA and Medicaid expansion by race/ethnicity that focused on low-income individuals showed a greater effect among the racial/ethnic minorities (Buchmueller et al. 2016; Courtemanche et al. 2019a; Courtemanche et al.

2019b; Fung et al. 2019; Sommers 2015).

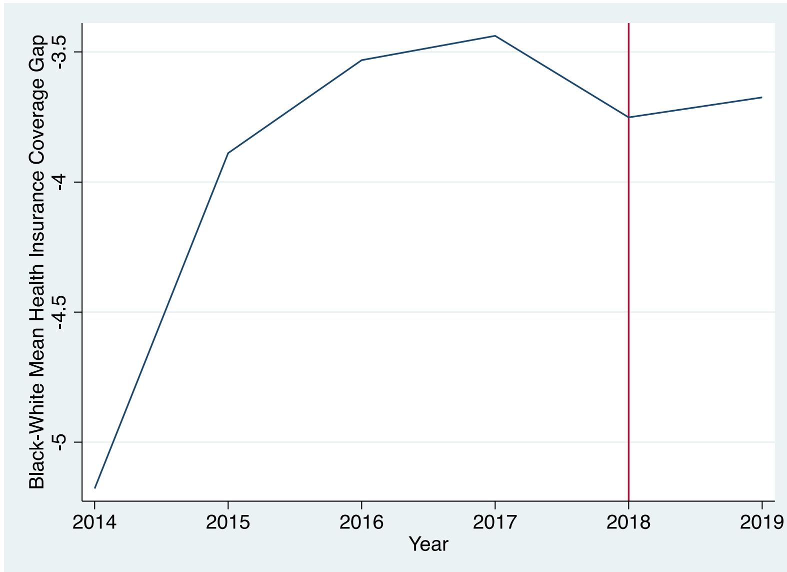

Figure 11. Black-White Economy-wide Gap

To further examine the effect of the state mandate on racial/ethnic disparity, I investigate the economy-wide gap by plotting the time series of the unadjusted (i.e., not including individual characteristics) racial coverage gap since 2014 (Figure 11). It is measured as the average health insurance coverage difference between Non-Hispanic Black and Non-Hispanic White individuals. The Black-White coverage gap first increases by 1.74 percentage points between 2014 and 2017, then decreases by 0.31 percentage points from 2017 to 2018. After the mandate, the coverage gap increases again by 0.08 percentage points. When the mandate is implemented is the inflection point where the coverage gap increases again, and the effect is small as expected.

Then, I plot the adjusted Black-White coverage gaps (i.e., $\beta_1 + \beta_k$) for treated and control states separately in Figure 12, with 2014 as the omitted year (i.e., β_1 is plotted for 2014). The regression results used to plot the graph are reported in Table 13. Generally, there is a level difference between the treatment and control states, but it gets smaller as time continues, then diverges again after the mandate. Before the mandate and conditional on observable characteristics,

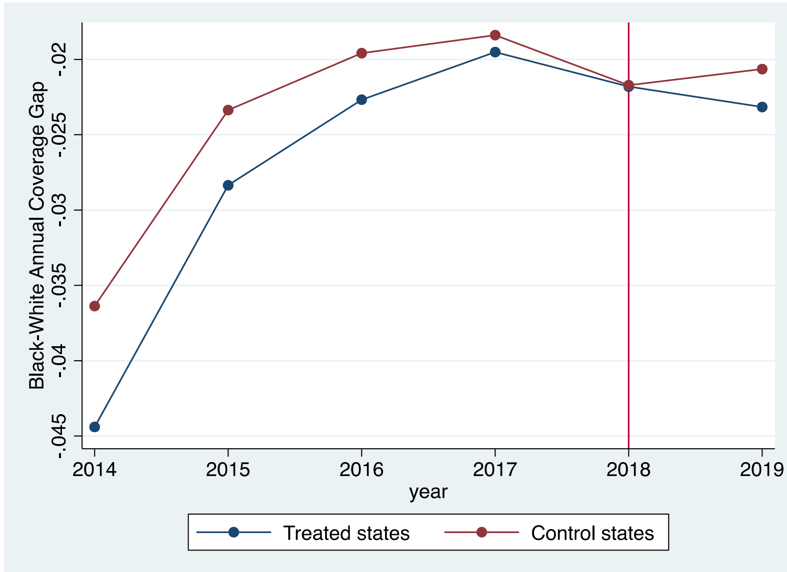

Figure 12. Adjusted Black-White Coverage Gaps

Table 13. The Effect of State Mandate on Black-White Coverage Gap

Variable	(1) Treatment states	(2) Control states
NHBlack	-0.0444*	-0.0364***
	(0.00648)	(0.00308)
1.NHBlack#2015.year	0.0160	0.0130***
	(0.00497)	(0.00245)
1.NHBlack#2016.year	0.0217	0.0168***
	(0.00620)	(0.00326)
1.NHBlack#2017.year	0.0249**	0.0180***
	(0.00168)	(0.00269)
1.NHBlack#2018.year	0.0226	0.0147***
	(0.00461)	(0.00290)
1.NHBlack#2019.year	0.0212	0.0157***
	(0.00573)	(0.00232)
Observations	227,569	5,585,662
R-squared	0.027	0.024
State FE	Yes	Yes
Year FE	Yes	Yes
Individual controls	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Non-Hispanic Black individuals had about 2–4.4% less coverage rate than Non-Hispanic White individuals in the treated states and about 1.8–3.6% in the control states. In addition, the trends of the treated and control states are similar before the mandate with the coverage gaps growing then slightly declining, but each evolving differently after the mandate. The Black-White coverage gap declines for the treated states whereas it increases for the control states. Similar to the unadjusted economy-wide gap, the mandate is an inflection point and improves the coverage gap relative to the trend that was occurring before. Such a result is consistent with my hypothesis that the state mandate will improve the racial/ethnic disparities. A small effect of the mandate on the coverage gap is also agreeing with the previous analyses.

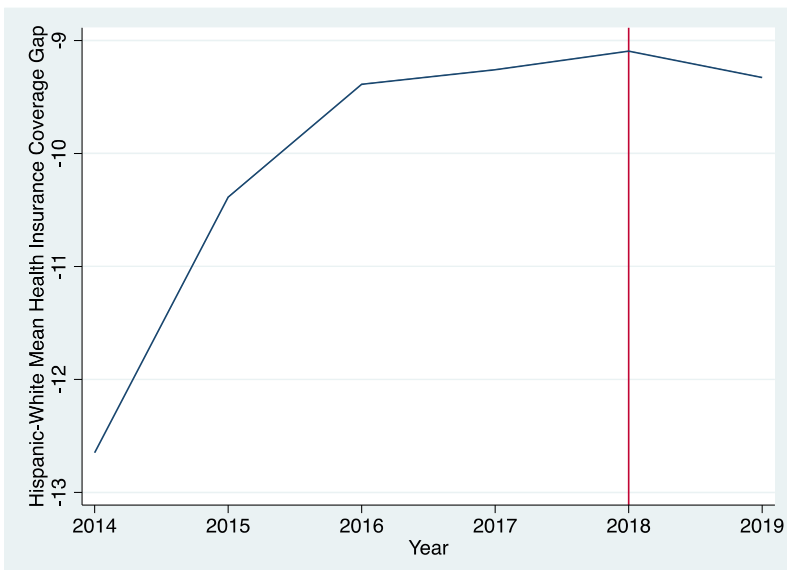

Figure 13. Hispanic-White Economy-wide Gap

A similar analysis is conducted with Non-Hispanic White and Hispanic individuals. Again, I examine the economy-wide Hispanic-White gap by plotting the time series of the unadjusted racial coverage gap since 2014. It is measured as the average health insurance coverage difference between Hispanic and Non-Hispanic White individuals (Figure 13). The Hispanic-White coverage gap first increases by about 3.6 percentage points between 2014 and 2018, then decreases by about 0.23 percentage points after the mandate. When the mandate is implemented is again the inflection point, and the coverage gap is decreasing. Once more, the fact that the effect is small was expected.

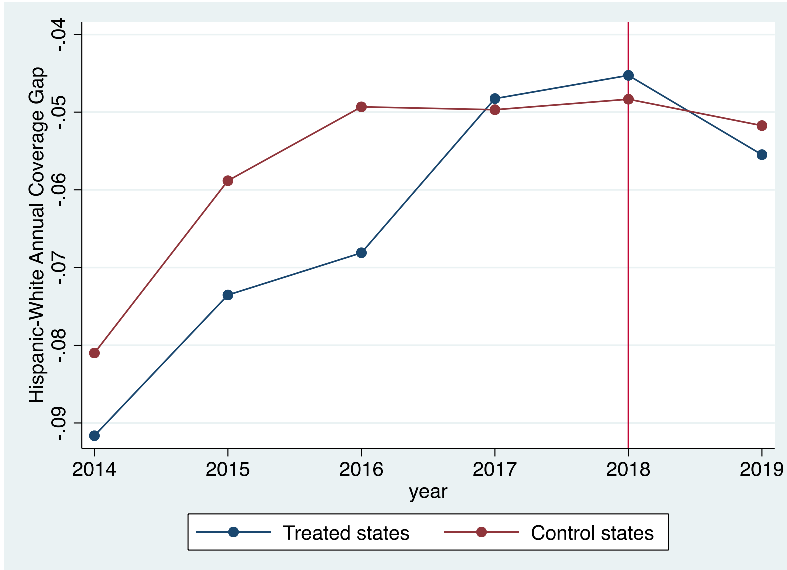

Figure 14. Adjusted Hispanic-White Coverage Gaps

Table 14. The Effect of State Mandate on Hispanic-White Coverage Gap

Variable	(1) Treatment states	(2) Control states
Hispanic	-0.0916***	-0.0810***
	(0.000964)	(0.00515)
1.Hispanic#2015.year	0.0181	0.0222***
	(0.00308)	(0.00454)
1.Hispanic#2016.year	0.0235**	0.0317***
	(0.00137)	(0.00553)
1.Hispanic#2017.year	0.0434*	0.0313***
	(0.00441)	(0.00789)
1.Hispanic#2018.year	0.0464**	0.0327***
	(0.00311)	(0.00834)
1.Hispanic#2019.year	0.0362	0.0293***
	(0.00731)	(0.00634)
Observations	235,017	5,920,205
R-squared	0.087	0.057
State FE	Yes	Yes
Year FE	Yes	Yes
Individual controls	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Then, I plot the adjusted Hispanic-White coverage gaps (i.e., $\beta_1 + \beta_k$) for treated and control states in Figure 14, with 2014 as the omitted year (i.e., β_1 is plotted for 2014). The results of the regression used to plot the graph are reported in Table 14. Before the mandate, there is generally a level difference between the treatment and control states, but it narrows by 2017. Then, it increases again but the coverage gap in treated states surpasses the gap in control states by 2018. Before the mandate and conditional on observable characteristics, Hispanic individuals had about 4.5–9.2% less coverage rate than Non-Hispanic White individuals in the treated states and about 4.8–8.1% less in the control states. Additionally, the trends of the treated and control states before the mandate are not as similar, but both are still following an increasing trend. Each evolves in the same direction after the mandate, but the decline of the Hispanic-White coverage gap is steeper for the treated states than for the control states. Before the mandate, the coverage gaps grow, and the trend changes when the mandate is implemented. The mandate again is an inflection point and improves the Hispanic-White coverage gap relative to the trend that is occurring before. Such a result is consistent with my hypothesis. Again, the conclusion is that the mandate had a small effect on improving the Hispanic-White coverage gap.

VI. Robustness Checks

A. Alternative Comparison Group

I select a comparison group to verify that the treatment effects are unique to the non-elderly individuals that are under the age 65. Because individuals above or at age 65 are exempt from the individual mandate, they can be used as a placebo group. Two same DD specifications are run, but individuals' age is limited to above or equal to 65. If the placebo test results are consistent with the main analysis, it would suggest my results are robust to state-specific policy changes that may affect levels of health insurance coverage in the states.

In Table 15, the results for Model 1 and Model 2 are very small and statistically insignificant. Furthermore, the effect on health insurance coverage after the state individual mandate is much smaller. For Model 1, there was a 0.0294 percentage point increase in coverage rates, which is smaller by approximately a factor of 17 than the main analysis. The impact for the second model was about 40 times smaller, with a 0.00771 percentage point increase.

Table 15. The Effect of State Mandate on Insurance Coverage for Individuals Above Age 65

Variable	(1) Model 1	(2) Model 2
Mandate x Post	0.000294	7.71e-05
	(0.000378)	(0.000403)
Observations	1,481,282	1,481,282
R-squared	0.033	0.033
State FE	Yes	Yes
Year FE	Yes	Yes
Individual controls	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B. Extended Model

Differences-in-differences Model 3: $Coverage_{ist} = \beta_0 + \beta_1 \, Mandate_s + \beta_2 \, Post_t + \beta_3 \, Mandate_s \times Post_t + \beta_x \mathbf{X}_{ist} + \delta_s + \tau_t + Unemp_{st} + Unemp_{st} \times Mandate_s + \varepsilon_{st}$

Event-study Model 3: $Coverage_{ist} = \beta_0 + \beta_1 \, Mandate_s + \sum_{k=2014}^{2019} \beta_2 \, \mathbf{1}\{K_{it} = k\} + \sum_{k=2014}^{2019} \beta_3 \, Mandate_s \times \mathbf{1}\{K_{it} = k\} + \beta_x \mathbf{X}_{ist} + \delta_s + Unemp_{st} + Unemp_{st} \times Mandate_s + \varepsilon_{st}$

Model 3 is a pre-post DD regression identical to Model 2 but with an unemployment interacted term, *$Unemp_{st}$ x $Mandate_s$*, additionally included as a control. Although including the interaction term is pushing the regression model far, it is still reasonable to include an unemployment interaction term to examine whether or not the effect of unemployment on health insurance differs depending on whether the state is in the treatment or control group. It could be that cyclical fluctuation in unemployment is different in New Jersey and Washington D.C. than it is in other states.

Table 16. The Effect of State Mandate on Insurance Coverage (Pooled)

Variable	(3) Model 3
Mandate x Post	-0.00117
	(0.000959)
Unemp	-0.00381
	(0.00259)
Unemp x Mandate	-0.00255**
	(0.00120)
Observations	7,266,452
R-squared	0.044
State FE	Yes
Year FE	Yes
Individual controls	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Result suggests that the state mandate decreased health insurance coverage by 0.117 percentage points, but the effect is statistically insignificant (Table 16). The event-study graph shows similar concern for pre-trend (Figure 15). However, the trend before the state mandate is increasing whereas the coefficient decreases after the mandate. For consistency, Model 3 is again run first with New Jersey and second with Washington D.C. as a treated state. After dropping Washington D.C. from the treated state, the state mandate has a negative and statistically significant 0.174 percentage point effect on health insurance coverage (Column 3, Table 17). After dropping New Jersey from the treated state, the state mandate increased coverage by 0.464 percentage points, and the effect is statistically significant at a 1% level (Column 4, Table 17). If multiple states are in the treated states, I would have more states to identify the difference in the effect of unemployment. But because there is one state in the treated group, I am pushing the data quite far. Both event-study graphs look qualitatively similar to other models, again with a concern for parallel-trend assumption (Figure 16 and Figure 17).

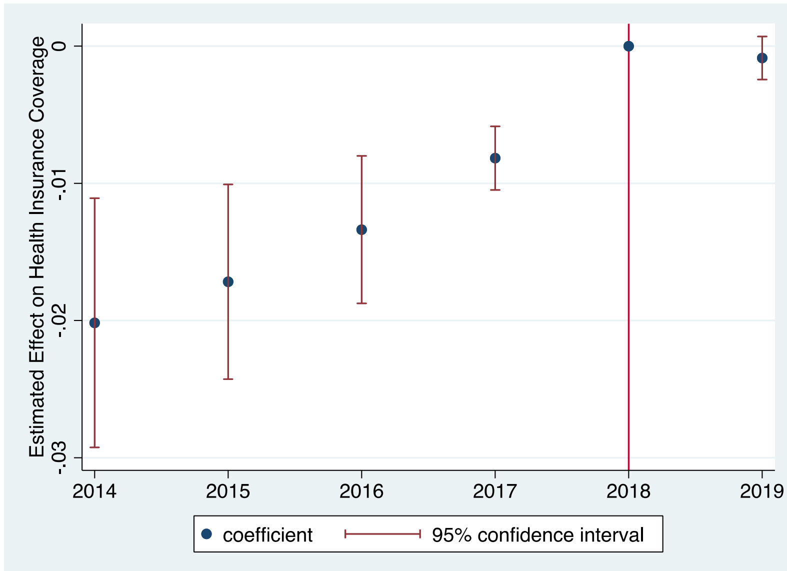

Figure 15. Event-study (Model 3, pooled)

Table 17. The Effect of State Mandate on Insurance Coverage

Variable	(3) Model 3 (New Jersey)	(4) Model 3 (Washington D.C.)
Mandate x Post	-0.00174***	0.00464***
	(0.000619)	(0.000814)
Unemp	-0.00384	-0.00386
	(0.00259)	(0.00259)
Unemp x Mandate	-0.00261**	-0.00239**
	(0.00120)	(0.000941)
Observations	7,245,193	6,990,035
R-squared	0.044	0.043
State FE	Yes	Yes
Year FE	Yes	Yes
Individual controls	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

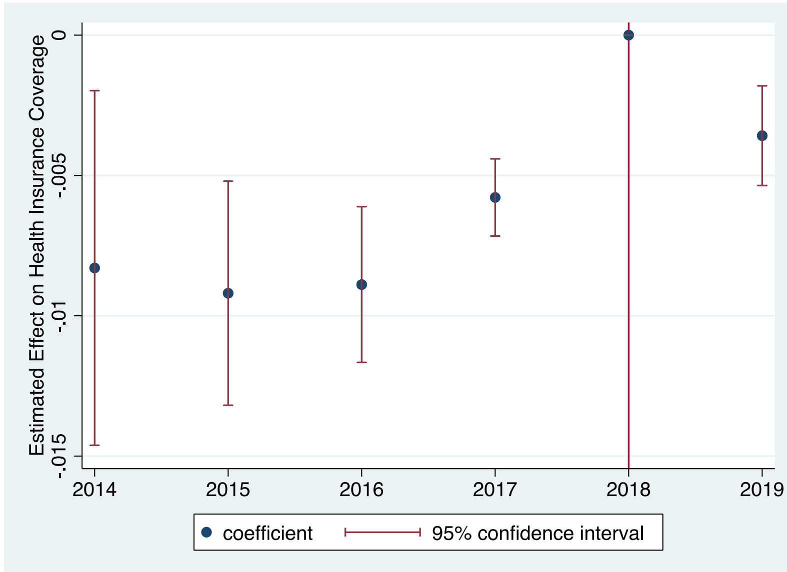

Figure 16. Event-study (Model 3, New Jersey)

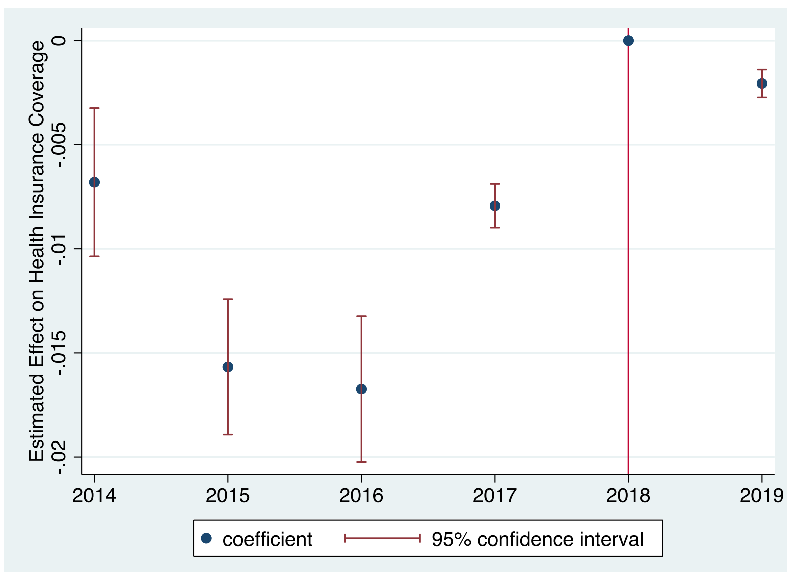

Figure 17. Event-study (Model 3, Washington D.C.)

VII. Conclusion

Despite the controversy of the individual mandate, there have been few studies due to the national implementation at the same time as ACA's other major coverage provisions. The recent federal individual mandate repeal without other simultaneous main provisions, the implementation of state mandate in New Jersey and D.C., and the restriction of subjects to high-income, non-elderly individuals who are neither exempt from the mandate nor eligible for subsidies help to directly analyze the mandate's effect on coverage rates and racial/ethnic coverage disparities. Using the 2014-2019 ACS and BLS data, I exploit the state-level variation and use a DD model to first compare the overall coverage rates between states with individual mandates and states without, then further compare them among different racial/ethnic groups. In my base model, I find a statistically significant 0.502 percentage point increase in health insurance coverage after state individual mandate. After controlling for unemployment rates, I find a consistent, but statistically insignificant 0.309 percentage point increase. If I break this down by state, New Jersey also suggests a 0.487 percentage point increase that is statistically significant while smaller and statistically insignificant 0.275 percentage points with the unemployment rate. The result for Washington D.C. is a 0.488 percentage point increase that is statistically significant, and a 0.726 percentage point increase that is also statistically significant after the unemployment rate is added. Because the event-study graphs for all models raise a concern for the parallel trend assumption and the health insurance coverage trends are different for all states, I implement synthetic control for New Jersey and Washington D.C. separately. New Jersey can find a good synthetic group, but the result is a negative effect of the mandate. On the other hand, synthetic Washington D.C. is less similar to Washington D.C., but the effect is positive. The results for both synthetic controls are statistically insignificant.

Stratifying the DD models by different racial/ethnic groups, I find that the racial/ethnic coverage disparity is reduced but by a small amount. Using the main model, the largest increase is among Hispanics, then Non-Hispanic Blacks, Non-Hispanic Whites, and Non-Hispanic other races. Results for all racial/ethnic groups are statistically significant. Adding unemployment rate as a control, Non-Hispanic Blacks experienced a larger increase in health insurance coverage than Non-Hispanic Whites, and Hispanics and Non-Hispanic other races experienced a smaller increase. The results are statistically significant for Non-Hispanic Blacks and Non-Hispanic Whites, while statistically insignificant for Hispanics and Non-Hispanic other races.

Furthermore, the Black-White economy-wide gaps increase then decrease slightly before the mandate. The gap starts to increase again after the mandate. After adjusting for individual characteristics and examining the trend for treatment and control states separately, the Black-White coverage gaps increase, then decrease in both treated and control states before the mandate. After the mandate, the Black-White coverage gap decreases for the treated states while it increases for the control states. Comparing before and after the policy, the mandate is improving the gap relative to the trend that is happening before. The result is consistent with my hypothesis, and the effect is small as expected. The Hispanic-White economy-wide gaps increase before the mandate and decrease afterward. The adjusted Hispanic-White coverage gaps for both treated and control states generally increase before the mandate, then both decrease after the mandate. But the decrease is steeper for the treated states while more gradual for control states. As with the Black-White adjusted coverage gap, the effect of the mandate on the Hispanic-White coverage gap is positive but small.

Overall, the state individual mandate had a small effect on increasing health insurance coverage and narrowing the racial/ethnic disparities. These modest effects may be that the mandate is not such a big treatment that I can capture. The sample included only the high-income individuals for whom the payments may not be that high to change their decision on health care enrollment. Additionally, the mean health insurance coverage rate of the sample is 93.9 percent, which means that there is only 6.1 percent of high-income individuals who are not insured. There is not much room left for the mandate to further increase the coverage rate.

My paper's key limitations are the lack of post-2019 data and the small sample size for each year, which makes the policy effect less statistically detectable. Due to the limited post-2019 data, I am only able to capture the short-term effect. As more reliable data become available for 2020 and onwards, future research could not only measure the longer-run effect of the mandate, but also further analyze the effect of Rhode Island, Vermont, and California's state mandate, which all took effect on January 1, 2020.

Although I find a small effect, the results suggest that state mandate can potentially be one tool to control the health insurance markets and insure the residents but not a primary and sole tool. In addition, they imply that it is important for policymakers to consider not only the aggregate coverage rates but further examine the differential effect on racial/ethnic minorities to develop tailored policy tools for them.

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Appendix

I. Summary statistics by racial/ethnic group

Table 1. Summary for Main and Control Variables (Non-Hispanic White)

Variable	N	Mean	Std. Dev.	Min	Max
Health Insurance Coverage	5290389	.955	.207	0	1
Year	5290389	2016.564	1.709	2014	2019
State	5290389	29.028	15.831	1	56
Gender	5290389	.493	.5	0	1
Marital status	5290389	3.283	2.363	1	6
Age	5290389	37.966	18.22	0	64
Citizen	5290389	.094	.46	0	3
White	5290389	1	0	1	1
Black	5290389	0	0	0	0
Hispanic	5290389	0	0	0	0
Other race	5290389	0	0	0	0
Race/ethnicity	5290389	1	0	1	1
FPL	5290389	909.012	666.896	400	17526.084
Education	5290389	2.905	1.338	1	5
Unemployment rate	5290389	4.648	1.11	2.3	8.2

Table 2. Summary for Main and Control Variables (Non-Hispanic Black)

Variable	N	Mean	Std. Dev.	Min	Max
Health Insurance Coverage	524911	.916	.277	0	1
Year	524911	2016.528	1.702	2014	2019
State	524911	27.667	15.198	1	56
Gender	524911	.508	.5	0	1
Marital status	524911	4.073	2.237	1	6
Age	524911	37.54	17.397	0	64
Citizen	524911	.274	.757	0	3
White	524911	0	0	0	0
Black	524911	1	0	1	1
Hispanic	524911	0	0	0	0
Other race	524911	0	0	0	0
Race/ethnicity	524911	2	0	2	2
FPL	524911	799.052	533.19	400	26632.996
Education	524911	2.744	1.262	1	5
Unemployment rate	524911	4.797	1.078	2.3	8.2

Table 3. Summary for Main and Control Variables (Hispanic)

Variable	N	Mean	Std. Dev.	Min	Max
Health Insurance Coverage	867067	.856	.351	0	1
Year	867067	2016.661	1.697	2014	2019
State	867067	23.135	17.696	1	56
Gender	867067	.488	.5	0	1
Marital status	867067	3.99	2.304	1	6
Age	867067	33.286	17.05	0	64
Citizen	867067	.83	1.208	0	3
White	867067	.727	.445	0	1
Black	867067	.021	.144	0	1
Hispanic	867067	1	0	1	1
Other race	867067	.252	.434	0	1
Race/ethnicity	867067	3	0	3	3
FPL	867067	813.683	545.372	400	18616.145
Education	867067	2.374	1.247	1	5
Unemployment rate	867067	4.825	1.121	2.3	8.2

Table 4. Summary for Main and Control Variables (Non-Hispanic Other Race: American Indian or Alaska Native, Chinese, Japanese, Other Asian or Pacific Islander, Other race)

Variable	N	Mean	Std. Dev.	Min	Max
Health Insurance Coverage	586657	.936	.245	0	1
Year	586657	2016.645	1.704	2014	2019
State	586657	23.494	17.371	1	56
Gender	586657	.521	.5	0	1
Marital status	586657	3.453	2.403	1	6
Age	586657	34.642	17.353	0	64
Citizen	586657	1.359	1.219	0	3
White	586657	0	0	0	0
Black	586657	0	0	0	0
Hispanic	586657	.029	.167	0	1
Other race	586657	.026	.16	0	1
Race/ethnicity	586657	4	0	4	4
FPL	586657	1003.368	732.091	400	16718.08
Education	586657	3.058	1.49	1	5
Unemployment rate	586657	4.884	1.144	2.3	8.2