The Effect of the Affordable Care Act (ACA) on educational outcomes among lower-income adults between 2003 and 2018

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Abstract

The Affordable Care Act (ACA) aimed to improve healthcare access, coverage, and insurance for lower-income, non-elderly American adults. This reform was implemented to reduce barriers to preventive healthcare, increase prescription drug use, and positively influence economic indicators such as GDP and employment rates. Previous studies have found that the ACA also helped decrease high school and college completion rates among students whose parents benefited from the reform. In this paper, we estimate the causal relationship between Medicaid expansion under the ACA and educational attainment among lower-income American adults, comparing states that expanded Medicaid with those that did not. Assuming the parallel trends assumption and exclusion restriction hold, we employ a Difference-in-Differences Instrumental Variable (DDIV) approach to assess the impact of Medicaid eligibility on enrollments. The results of our study indicate some abstract trends and highlight the need for further in-depth research, as factors beyond the ACA—such as other unobserved confounders—may also contribute to changes in educational outcomes during this period.

Contents

1 Introduction

1.1 Background

The Affordable Care Act (ACA), enacted on March 23 in 2010, was a landmark policy designed to increase healthcare access for millions of uninsured Americans, particularly targeting lower-income, non-elderly adults. One of its key components, Medicaid expansion, was implemented at the state level, creating natural variations that provide fertile ground for examining the broader impacts of improved healthcare access. This paper aims to address a critical question: How did Medicaid expansion under the ACA impact educational attainment among lower-income American adults? Specifically, we focus on whether improved healthcare access influenced enrollment and completion rates in higher education.

Healthcare and education are often treated as separate policy domains, but their impacts are deeply interwoven. The decision to continue or pursue further education can be heavily influenced by health-related factors, particularly for economically disadvantaged groups. Prior studies have highlighted that individuals with consistent access to healthcare are more likely to complete higher levels of education. This connection is likely mediated by several mechanisms: healthier individuals are less burdened by chronic conditions, better able to concentrate on their studies, and more likely to engage in longer-term planning, such as pursuing degrees. Therefore, understanding the relationship between Medicaid expansion and educational attainment can offer crucial insights for policymakers aiming to address both healthcare inequities and barriers to educational success.

According to Stateline, nearly 20% of uninsured working-age adults live in states that have not expanded Medicaid under the ACA. These individuals earn too much to qualify for Medicaid or too little to receive financial assistance to purchase insurance, affecting 1.6 million adults, over 60% of whom are people of color. This "coverage gap" leaves many low-income individuals without access to healthcare, despite the ACA's intent Mangan and Saloner (2019). Many of these individuals endure serious medical crises without adequate health coverage, which underscores the critical role Medicaid expansion could play in reducing poverty and improving key health outcomes, such as mortality rates and life expectancy.

Moreover, while the ACA and Medicaid Expansion were primarily targeted at adults, children have also been indirectly affected. Garfield et al. (2020) reported the uninsured rate of children fell from 7.1% in 2013 to 6.0% in 2014, with even steeper declines in Medicaid expansion states. Yeung (2020) further illustrated that these gains are attributed to "welcome mat" effects, where outreach and enrollment activities increased awareness of Medicaid for adults and, by extension, their children. Additionally, parents with Medicaid are better protected from financial catastrophes, which allows them to create a more stable environment for their children.

1.2 Research purpose and organization

Medicaid expansion was implemented unevenly across the United States, with some states opting in and others remaining out. This division presents a unique opportunity to evaluate the causal impact of Medicaid expansion on educational outcomes using quasi-experimental methods. We apply a Difference-in-Differences Instrumental Variable (DDIV) approach to exploit the natural variation in Medicaid expansion among states. This approach allows us to control for unobserved factors that might influence educational outcomes and identify whether Medicaid eligibility effectively served as an instrument for increased educational attainment. Our findings indicate that Medicaid expansion has a significant, positive effect on educational outcomes, particularly through its impact on mental health. Mental health improvements, in particular, appear to play a critical role in facilitating higher enrollment rates and reducing dropout rates.

Motivating this analysis are the broader societal benefits of educational attainment, which include higher future income, improved health outcomes, and enhanced civic participation. The decision to expand Medicaid has the potential to create ripple effects, positively affecting not only individual beneficiaries but also the communities in which they live. By providing health security, the ACA's Medicaid expansion may alleviate some burdens that often prevent individuals from completing their education, such as health emergencies and associated financial strain. A more educated population, in turn, contributes to a stronger workforce, reduced public assistance dependency, and a more engaged citizenry.

The findings of this paper could inform ongoing policy debates regarding the ACA and future healthcare reforms. If Medicaid expansion positively affects educational attainment, this would provide additional justification for expanding access to healthcare. Such results would not only underline the importance of healthcare for individual health outcomes but also demonstrate its broader societal value in improving education, economic opportunities, and overall well-being. By clarifying the relationship between healthcare access and educational outcomes, this research seeks to contribute to a more nuanced understanding of the multifaceted benefits of healthcare reforms.

The rest of the paper is divided as follows. Section 2 reviews the literature on Medicaid expansion eligibility under the ACA, its impact on health and education outcomes, and the potential econometric methods used, addressing uncertainties and solutions regarding key assumptions. Section 3.4 presents the instrumented Difference-in-Differences (DID-IV) methodology and the empirical strategy employed in our study. Section 4 describes the data, detailing the sources and data treatment methods. Section 5 presents the main results and their interpretations. Finally, Section 6 summarizes the key findings, highlights their significance and implications, and illustrates potential directions for future research.

2 Literature review

2.1 Related to Medicaid eligibility, its impact on health outcomes

Much of the existing literature has concentrated on the health and labor market impacts of the ACA with Medicaid expansion. For example, Serakos and Wolfe (2016) focuses on the impact of Medicaid eligibility on healthcare access, health, and labor market outcomes among young adults, finding that the ACA had positive economic, social, and health effects. Simon et al. (2016) examines the causal effect of the ACA on preventive healthcare and health behaviors, including self-assessed health, using a quasi-experimental research design. The study finds an increase in insurance coverage by 17%, significant improvements in self-assessed health (general, mental, and physical health indicators), and a decrease in preventive healthcare usage. Additionally, they argue that the ACA's goal of increasing benefits for lower-income childless adults could potentially disadvantage other lower-income individuals, who may receive fewer incentives from the expansion.

Some studies have found that Medicaid expansions lead to improvements in self-reported health (Sommers et al. (2012); Finkelstein et al. (2012); Barbaresco et al. (2015)). However, other research has found minimal evidence of health improvements, potentially due to individual differences in preferences for preventive measures and routine healthcare. Wehby et al. (2018) highlight the role of genetics in preventive care, while Wherry and Miller (2016) find an insignificant causal effect on self-assessed health in the context of the 2014 Medicaid expansion.

2.2 Related to Medicaid eligibility, its impact on Educational outcomes

Beyond healthcare, researchers have explored the ACA's potential impact on educational outcomes. The ACA's influence on educational attainment, academic performance, and college graduation rates is largely understood through the mechanisms of improved health insurance coverage, reduced financial stress, and better mental and physical health outcomes for students and their families.

The ACA's Medicaid expansion and the introduction of health insurance marketplaces significantly increased health insurance coverage for young adults and their families. One key provision, allowing young adults to remain on their parents' insurance until age 26, has been linked to improvements in educational attainment. Studies by Barbaresco et al.

(2015) focus on young adults covered by their parent's insurance were more likely to pursue postsecondary education. The reduction in healthcare-related financial risk enabled families to reallocate resources to educational expenses, supporting the pursuit of higher education.

Research by Gross and Notowidigdo (2011) finds that Medicaid expansion helped low-income families stabilize their finances, resulting in fewer disruptions to children's schooling. Reduced out-of-pocket medical expenses enabled families to avoid making trade-offs between healthcare and education, leading to more consistent school attendance and higher graduation rates.

Access to healthcare has also been shown to improve academic performance through better physical and mental health. Miller and Wherry (2019) demonstrate that children from families gaining coverage under the ACA experienced fewer health problems, leading to better school attendance and higher test scores. Improved mental health, facilitated by access to mental health services covered under the ACA, played a critical role in enhancing students' cognitive function and academic engagement.

Moreover, Bullinger et al. (2023) shows that children with insured parents were more likely to succeed academically, as parental health coverage reduced the likelihood of economic hardship and stress within the household. This stability allowed students to focus more on their studies, resulting in improved grades and test scores, finding a roughly 2% improvement in reading test scores, though there were no significant effects on other test scores or socioemotional metrics. It is important to note that this analysis was limited to data from lower-income families, which could introduce bias due to the indirect effects of parental health insurance coverage on children.

2.3 Related to econometric methods

The econometric approach of difference-in-differences (DiD) is frequently used to estimate causal relationships, particularly in evaluating policy interventions. This method has been widely applied in the literature to evaluate the effects of Medicaid expansions on health and educational outcomes. Instrumented difference-in-differences (IV-DiD) is a useful extension when there is a need to address potential endogeneity in treatment assignment.

A commonly cited study that uses the DiD approach to evaluate the ACA's impact is Sommers et al. (2012), which examined the impact of Medicaid expansions on health outcomes. By comparing health metrics in states that expanded Medicaid to those that did not, the authors found significant improvements in self-reported health and access to care. Finkelstein et al. (2012) utilized a similar DiD strategy in their study of the Oregon Health Insurance Experiment to estimate the causal effect of gaining Medicaid coverage on health outcomes. Their findings showed that Medicaid coverage led to increased healthcare utilization, better self-reported health, and reduced financial strain.

Another example of applying DiD to educational outcomes is the work by Cohodes et al. (2016), who studied the effects of Medicaid eligibility on children's educational attainment. By employing a difference-in-differences framework, they established a causal link between expanded Medicaid eligibility and improved high school graduation and college enrollment rates. They found that Medicaid eligibility during childhood led to increased rates of high school completion and college attendance, suggesting that health coverage can have long-term educational benefits.

Instrumented difference-in-differences approaches can be applied to address potential endogeneity and threats to validity. These methods use exogenous policy changes as instruments to assess the impact of health outcomes on educational outcomes, helping to mitigate biases from unobserved confounders that may influence both health insurance coverage and academic outcomes. With a sufficiently large and well-defined treatment and control group, and assuming that the health reform does not lead to significant changes in variables of outcomes, the parallel trend assumption of DiD can be maintained. Furthermore, the exclusion restriction assumption is more likely to hold, as there could be a minimal correlation between access to healthcare access and educational enrollment rates. We will further delve into this in section 3.2 and section 4.3 to check and see whether these two assumptions hold or not.

3 Empirical strategy: Instrumented Difference-in-Differences

3.1 Main ideas

The main econometric method employed in this analysis is the instrumented difference-in-differences (IV-DiD or DDIV). This approach combines the strengths of instrumental variable (IV) analysis and difference-in-differences (DiD) to address potential unmeasured confounding and obtain consistent estimates of treatment effects. The primary advantage of using IV-DiD lies in its ability to leverage exogenous variation introduced by an instrument to validate the treatment effect while controlling for unobserved biases, a key challenge in observational studies.

In our context, we are interested in how the treatment (Medicaid eligibility) affects educational outcomes (e.g., enrollment rates, number of enrollments, graduation rates). By using an instrumented variable, such as a policy-induced health eligibility change, we can isolate the exogenous portion of variation that influences health outcomes but is not directly related to educational outcomes, allowing us to make causal inferences with greater confidence. The DDIV estimate represents a weighted average causal effect of treatment on the population, similar to the local average treatment effect (LATE) estimated in standard IV frameworks (Hudson et al., 2017).

3.2 Monotonicity&Exclusion restriction&Parallel trends

The validity of the IV-DiD approach hinges on several critical assumptions, namely parallel trends, exclusion restriction, and monotonicity:

Parallel Trends: This assumption requires that, in the absence of treatment, the outcome variables for both the treatment and control groups would follow similar trajectories over time. For the DDIV estimator, this assumption must hold for both the treatment assignments

(Medicaid eligibility)[1] and the educational outcomes[2], meaning pre-existing trends should be identical for both the treated and control groups before the intervention.

Exclusion Restriction: The chosen instrument must affect the outcome only through its impact on the treatment. In our case, this means that the health policy changes should influence educational outcomes only through their effect on health status, and not through any other channels.

$$Z \perp (D_t^{(0)}, D_t^{(1)}, Y_1^{(0)} - Y_0^{(0)}), t = 0, 1 | X)$$

Monotonicity: The instrument must uniformly encourage treatment uptake across the population. This implies that no subgroup experiences a negative effect from the instrument (i.e., no defiers). In our study, this assumption can be justified by the uniform effect of Medicaid expansions in encouraging healthcare utilization, which subsequently leads to better health outcomes.

$$E(Y_1^{(1)} - Y_1^{(0)} | X) = E(Y_0^{(1)} - Y_0^{(0)} | X)$$

The IV-DiD approach helps relax some of the more stringent assumptions of standard DiD methods, particularly in addressing potential violations of the parallel trends assumption due to unmeasured time-varying confounders. By exploiting an exogenous encouragement (e.g., policy change), we can extract the causal effect even when some assumptions are disputed in traditional settings.

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[1]
$$E(D_1^{(1)} - D_0^{(1)} \mid Z = 1, X) \neq E(D_1^{(0)} - D_0^{(0)} \mid Z = 0, X)$$
$$= E(D \mid T = 1, Z = 1, X) - E(D \mid T = 0, Z = 1, X) \neq E(D \mid T = 1, Z = 0, X) - E(D \mid T = 0, Z = 0, X).$$

[2]
$$E(Y_1^{(1)} - Y_0^{(1)} \mid Z = 1, X) \neq E(Y_1^{(0)} - Y_0^{(0)} \mid Z = 0, X)$$
$$= E(Y \mid T = 1, Z = 1, X) - E(Y \mid T = 0, Z = 1, X) \neq E(Y \mid T = 1, Z = 0, X) - E(Y \mid T = 0, Z = 0, X)$$

Y = Outcome variables, X = Covariates, D = Treatment assignment indicators, Z = Instrument variables, T = Pre-Post time indicators.

3.3 Control variables selection

To ensure robustness, we include several key control variables in our empirical model. These controls are selected to account for observable characteristics that may influence both the treatment and outcome variables. Specifically, we include demographic factors such as age, gender, socioeconomic status, parental education, and geographic region. These factors serve two purposes:

1. To account for potential confounding variables that might simultaneously affect health and educational outcomes.

2. To improve precision in estimating the treatment effect by reducing residual variance in the outcome.

Including these covariates is essential, particularly in maintaining the validity of the exclusion restriction and ensuring that the parallel trends assumption holds conditional on these controls.

3.4 Modeling

The model specification involves estimating a two-stage system where the first stage regresses the treatment on the instrument and the covariates, and the second stage uses the fitted values from the first stage to estimate the impact on the outcome variable. Formally, we proceed as follows:

First Stage:

$$Q_{st} = \gamma_s + \delta T_t + \pi Z_s T_t + \omega x_{st} + \eta_{st} \tag{1}$$

Here, represents the health outcome variables (e.g., self-assessed health indicators(physical health, mental health, preventive health car) is the binary instrument that varies over time. The coefficient measures the extent to which the policy influences the treatment (health outcomes) over time.

Second Stage:

$$Y_{st} = \alpha_s + \tau T_t + \beta \hat{S} st + \omega x_{st} + \epsilon_{st} \tag{2}$$

In this equation, denotes the educational outcome (e.g., enrollment rate), while represents the causal impact of health outcomes on educational outcomes. The DDIV estimator can be obtained by taking the ratio of the reduced form and the first-stage coefficients, providing a measure of the average causal effect on the treated population.

Estimated DDIV Estimator: The estimated DDIV estimator is given by:

$$\hat{\beta}_{DDIV} = \frac{E[Y_{s1} - Y_{s0} \mid D_s = 1] - E[Y_{s1} - Y_{s0} \mid D_s = 0]}{E[Q_{s1} - Q_{s0} \mid D_s = 1] - E[Q_{s1} - Q_{s0} \mid D_s = 0]} \tag{3}$$

Where Q_s represents the instrument, i.e., Medicaid expansion status.

This estimator represents the average causal effect of the treatment (health outcomes) on the educational outcome for individuals whose treatment status is influenced by the instrument (i.e., the local average treatment effect). The numerator captures the reduced form relationship between the instrument and the outcome, while the denominator captures the effect of the instrument on the treatment. By taking the ratio, we obtain an estimate of the causal impact of the treatment on the outcome, addressing the issue of endogeneity in the original treatment-outcome relationship.

4 Data

4.1 Data Sources

We utilize data from the Behavioral Risk Factor Surveillance System (BRFSS), a nationally representative cross-sectional survey conducted annually from 2003 to 2018. This dataset contains approximately 400,000 individual records annually, providing information on respondents' state, income, and health-related behaviors. We focus on low-income households (earning less than 138% of the Federal Poverty Line) and individuals aged 25 to 64. To address potential biases arising from income fluctuations near the federal poverty threshold, we will include demographic controls such as age, sex, BMI, race, and other socioeconomic indicators. The main instruments will be self-assessed health outcomes, including a five-category general health scale and mental and physical health measures. In addition to BRFSS data, we incorporate enrollment data from the National Student Clearinghouse Research Center, which tracks coverage rates at Title IV-eligible institutions. This dataset spans enrollment rates for private and public colleges from 2004 to 2020, providing detailed insight into enrollment patterns across different institutional sectors. Given that the resources for these two datasets are reliable organization and the data are time-series and cross-sectional, the causal effect estimation would still be acceptable.

I aggregated the variables by calculating the mean for each year across 14 years, from 2004 to 2018, covering approximately 51 distinct states, resulting in 761 observations. Overall, I have around 91 variables. Despite some states adopting Medicaid expansion later than the actual reform in March 2014, it is appropriate to assume that the earliest effects began with the initial implementation date of the reform. As a result, there are 19 control states and 32 treatment states.

```
# Sum 'records' by 'treatment' and 'pre_post'
summary = merged_total.groupby(['treatment', 'pre_post'])['records'].sum()

# Print the sums for each group
print("Non-expansion (treatment = 0, pre_post = 0):", summary.loc[(0, 0)])
print("Expansion (treatment = 1, pre_post = 0):", summary.loc[(1, 0)])
print("Non-expansion (treatment = 0, pre_post = 1):", summary.loc[(0, 1)])
print("Expansion (treatment = 1, pre_post = 1):", summary.loc[(1, 1)])
```

```
Non-expansion (treatment = 0, pre_post = 0): 32921
Expansion (treatment = 1, pre_post = 0): 44847
Non-expansion (treatment = 0, pre_post = 1): 5467
Expansion (treatment = 1, pre_post = 1): 8194
```

In total, we have 91,429 samples across 14 years. The figure above shows the number of samples for each group—treatment, control, pre-treatment, and post-treatment.

Variable		**Before ACA**		**After ACA**	
		Medicaid Expansion	**Non-expansion**	**Medicaid Expansion**	**Non-expansion**
Age	Mean	39.78	39.633	43.906	43.711
	SD	(2.869)	(3.513)	(3.394)	(3.287)
Average number of	Mean	5.041	5.078	5.230	5.237
Household sizes	SD	(0.234)	(0.289)	(0.396)	(0.390)
Percentage of federal	Mean	76.591	75.338	70.936	70.765
poverty level	SD	(6.543)	(6.543)	(7.893)	(7.642)
Days not in good mental	Mean	14.222	14.431	15.146	15.158
in past month	SD	(1.785)	(1.634)	(2.475)	(2.279)
Overall BMI	Mean	0.212	0.150	0.211	0.150
≥ 30	SD	(0.118)	(0.143)	(0.147)	(0.172)
BMI	Mean	27.719	27.846	28.238	28.474
	SD	(0.723)	(0.553)	(1.091)	(0.971)
Days not in good physical	Mean	12.596	12.561	14.08	13.593
in past month	SD	(1.662)	(1.631)	(2.298)	(2.241)
Overall health very good	Mean	0.211	0.206	0.175	0.150
or excellent	SD	(0.056)	(0.056)	(0.082)	(0.087)
Overall health very good, good	Mean	0.531	0.530	0.475	0.481
or excellent	SD	(0.076)	(0.085)	(0.105)	(0.109)
Enrollment Rates	Mean	0.914	0.934	0.973	0.971
Rates	SD	(0.076)	(0.060)	(0.021)	(0.025)
Number of Enrollments	Mean	397,462	352,758	395,911	379,368
(In thousands)	SD	(487,650)	(332,727)	(552,109)	(371,352)

Table 1: Summary Statistics of Dependent/Independent Variables by State Medicaid Expansion Status and Pre-Post Treatment

4.2 Summary Statistics Interpretation

Age: The average age is 39.8 years for Medicaid Expansion states and 39.6 years for Non-expansion states before the ACA. After ACA, the average age increases slightly to 43.91 years in Expansion states and 43.71 years in Non-expansion states, reflecting the demographic shifts post-ACA.

Household size: The average household size is stable at around 5 people in both groups before and after the ACA. The variability is low (SD of around 0.23 for Expansion and 0.29 for Non-expansion), indicating that household sizes do not fluctuate much across states or over time.

Federal Poverty Level: The average percentage of the federal poverty level is 76.6% in Medicaid Expansion states before the ACA, compared to 75.3% in Non-expansion states. Post-ACA, both groups see a decrease in the poverty level to 70.94% in Expansion states and

70.77% in Non-expansion states, likely due to the Medicaid expansion improving economic conditions.

Mental Health (Days not in good mental health): The average number of days with poor mental health is 14.2 before the ACA in both groups, with a slight increase post-ACA (to 15.1 in both groups). The standard deviations show more variability post-ACA, especially in Non-expansion states, indicating a wider range of mental health outcomes.

Obesity (BMI $\geq$ 30): The proportion of individuals with obesity is slightly higher in Medicaid Expansion states (21.2%) compared to Non-expansion states (15%) before the ACA, and remains similar post-ACA. The variation is low, suggesting consistent obesity patterns across states.

BMI: The average BMI increases slightly post-ACA in both groups, from 27.7 before the ACA to 28.2 in Expansion states and 28.5 in Non-expansion states. The variation in BMI increases post-ACA, particularly in Non-expansion states, suggesting more diversity in BMI values.

Physical Health (Days not in good physical health): The average number of days spent in poor physical health is very similar between Medicaid Expansion (12.6) and Non-expansion (12.6) states before the ACA, with a slight increase post-ACA (to 14.08 in Expansion and 13.59 in Non-expansion states). The standard deviation increases post-ACA, showing more variation in health outcomes.

Health (Very Good or Excellent): The proportion of individuals reporting very good or excellent health is slightly higher in Medicaid Expansion states (21.1%) compared to Non-expansion states (20.6

Health (Very Good, Good, or Excellent): The proportion of individuals reporting good health is stable across both groups, with a slight decrease post-ACA, reflecting changes in health perceptions over time. The variation is low, indicating consistent ratings of health across states.

Enrollment Rates: The enrollment rates increase significantly post-ACA, especially in

Medicaid Expansion states (from 91.4% to 97.3%), while Non-expansion states see a smaller increase (from 93.4% to 97.1%). The variability in enrollment rates increases post-ACA, suggesting greater disparities in enrollment patterns across states.

Number of Enrollments: Medicaid Expansion states show higher average enrollments (397,462) compared to Non-expansion states (352,758) before the ACA. The variation in enrollments is large (SD of 487,650 in Expansion states), reflecting substantial differences in enrollment numbers across states.

Overall, Medicaid expansion has led to notable changes in health and healthcare access, with some health improvements and higher enrollment rates in Expansion states. Non-expansion states show less pronounced changes. The data indicates moderate to high variation in some health outcomes post-ACA, particularly in terms of physical health and enrollment rates.

5 Results

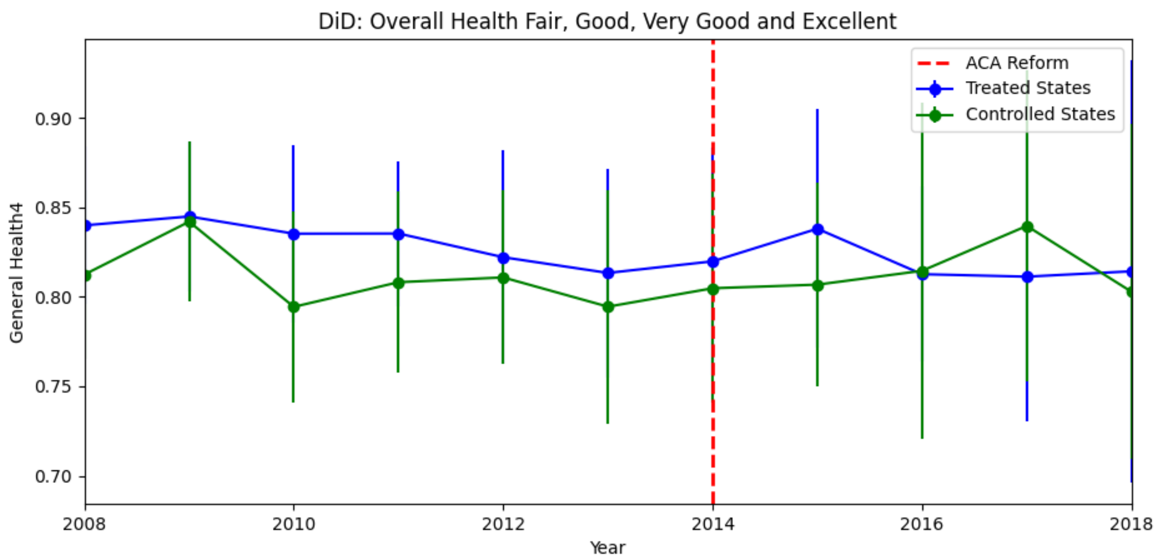
```
for (i in seq_along(first_stage_formulas)) {
  model <- lm(first_stage_formulas[[i]], data = clean, weights = clean$records)
  first_stage_models[[i]] <- model
  clean[[paste0("predicted_health_", i)]] <- predict(model)
}
cat("Predicted days in bad physical days")
cat("\n")
print(head(clean$predicted_health_2))
cat("\n")
cat("Predicted overall health for poor=0")
cat("\n")
print(head(clean$predicted_health_6))
```

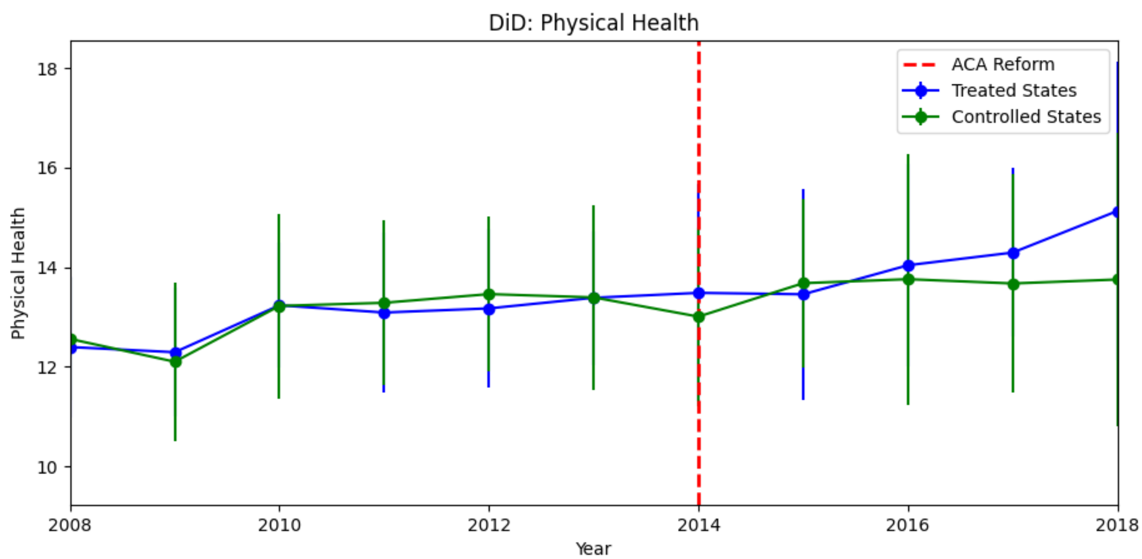
```
Predicted days in bad physical days
       1        2        3        4        5        6 
12.05574 12.06432 12.06432 12.06432 12.06432 12.06432 

Predicted overall health for poor=0
        1         2         3         4         5         6 
0.8291943 0.8496939 0.8496939 0.8496939 0.8496939 0.8496939 
```

As we defined our equation in our empirical strategy section. In the first stage, we will run a DiD regression using health outcomes (self-reported health with respect to days in the past month (bad physical, mental health, Indicator of Obesity(BMI $\geq$ 30), and an indicator of general health with a scale of 5 from poor to excellent. In the Second Stage, based off using the "predict" command of R, we will estimate the the impact of following predicted health outcomes on enrollment rates and number of enrollments. In our regression, we clustered standard errors by state. Moreover Since we used the mean values for all health outcomes of each city recordance therefore for one unique state with corresponding year there are a lot different records, therefore we will adjust the weight by the records of that specific value.

5.1 DiD plot & First Stage





- In the top plot, both treated and control states follow approximately parallel trends before the ACA implementation, suggesting the parallel trends assumption is likely satisfied. This adds credibility to the DiD model as it demonstrates that both groups were evolving similarly before the intervention. After the ACA reform, there is a noticeable decline in the proportion of individuals reporting "excellent, very good, good, fair" health in both treated and control states. However, the treated states appear to have a slightly less pronounced decline compared to control states, which suggests that Medicaid expansion may have mitigated the deterioration of self-reported health to some extent. The error bars indicate substantial variability, with significant overlap between treated and control states. This overlap implies that while the average trend may differ, the confidence in detecting a significant treatment effect is limited due to high variability across states and years

- The bottom plot illustrates the trend in days of poor physical health per month. Before the ACA, treated and control states generally exhibited parallel trends, supporting the validity of the DiD model. Post-ACA, treated states experienced a decrease in days of poor physical health immediately following the intervention, suggesting a potential positive impact of Medicaid expansion on physical health. However, by 2016, the trend appears to reverse, with an increase in days of poor physical health. This fluctuation could be attributed to the delayed effects of healthcare improvements or varying state-level factors that influence health beyond Medicaid coverage. Again, the overlapping error bars highlight considerable variability, indicating that there is uncertainty in the precision of the treatment effect, particularly in the years after the ACA's introduction.

Overall, while the results suggest some improvements in health outcomes immediately after Medicaid expansion, the considerable variability across states and overlapping error bars point to challenges in confidently attributing these effects solely to the ACA reform.

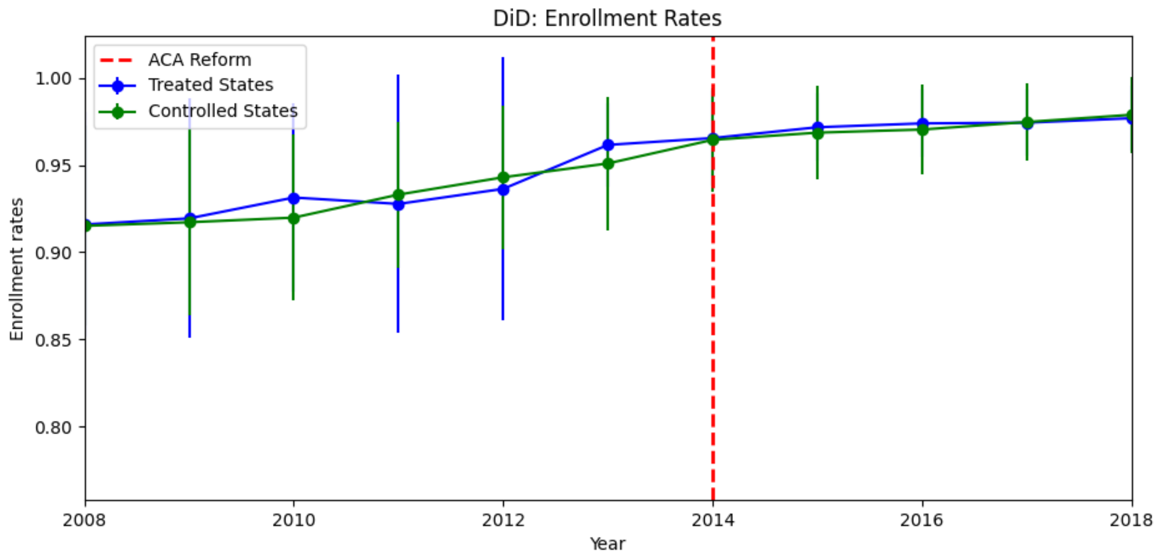
1. **Relevance Assumption**

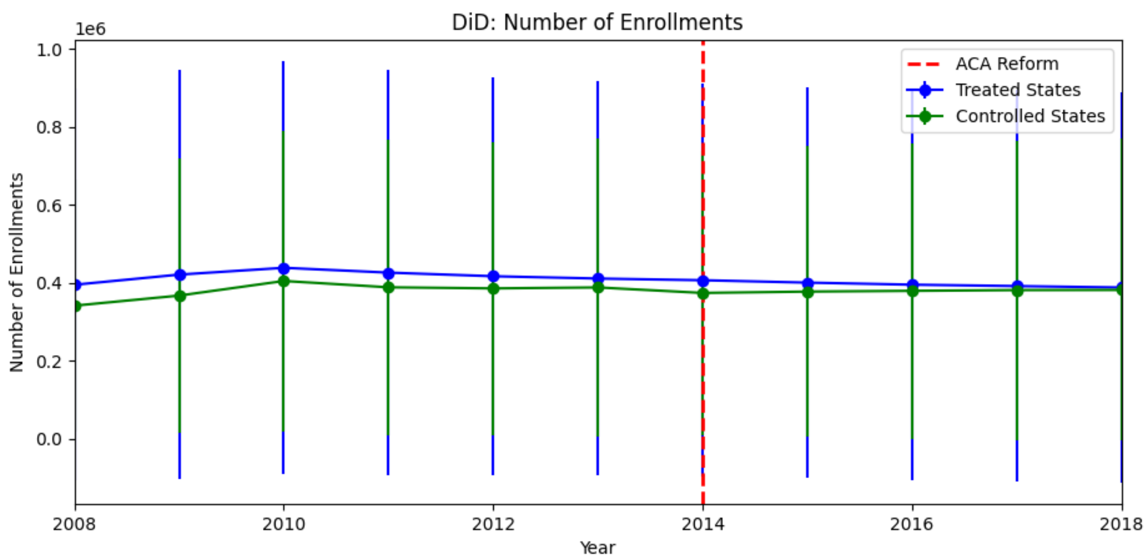
   The relevance assumption is confirmed by examining the F statistics for each health outcome presented in Table .4, .5. The F-statistics range from 5.106 to 132.004, and many are highly significant at the 1% level (indicated by ***). This shows that Medicaid eligibility is strongly correlated with health outcomes such as access to healthcare and days in poor mental health. The high F statistics for most health outcomes indicate that the instrument (Medicaid expansion) is powerful in explaining variation in these health measures, thus satisfying the relevance assumption for an effective instrumental variable approach. This suggests that Medicaid eligibility meaningfully impacts these health outcomes, which justifies its use as an instrument in our model.

2. **Exclusion Restriction**

   The exclusion restriction requires that Medicaid expansion should only affect enrollment rates through its impact on healthcare access and health outcomes, and not through any other channels. This assumption is supported by controlling for observable factors such as age, and by focusing on pre- and post-reform comparisons. However, it is recognized that there may be unobservable factors (e.g., regional economic shocks or unmeasured health policies) that could influence both health outcomes and enrollment rates, potentially violating this assumption.

5.2 DiD plot &Second Stage





Enrollment Rates

- Trends Pre- and Post-ACA: Both treated and control states experienced an upward trend in enrollment rates before and after the ACA. The trends appear to be roughly parallel prior to the ACA implementation, suggesting that the parallel trends assumption is plausible.

- : Effect Post-ACA: After the ACA, the treated states' enrollment rates continue to increase at a similar pace compared to control states. The slight divergence indicates a marginal effect of Medicaid expansion on boosting enrollment rates. However, given the overlapping error bars, this difference is not highly significant, suggesting high variability and difficulty in precisely estimating the treatment effect.

Number of Enrollments

- Trends Pre- and Post-ACA: BBoth groups showed similar trends in the number of enrollments, with no substantial divergence post-ACA. The treated and control groups remained almost parallel post-intervention, implying that the ACA reform did not substantially affect the number of enrollments in treated states relative to the controls.

- Effect Post-ACA: After the ACA, While there is an observable increase in the number of enrollments, the magnitude of the increase is similar between the treated and control groups, indicating minimal additional effect attributable solely to Medicaid expansion.effect.

Second Stage Regression Results without control

The second-stage regression results for predicting enrollment rates and the number of enrollments using various health outcomes as instruments are presented in Table .6. The results highlight the relationship between predicted health outcomes (such as access to healthcare, self-reported health status, and BMI) and enrollment outcomes.

- Enrollment Rates: Most health outcomes significantly affect enrollment rates. Notably, better self-reported health outcomes ("Overall Health Excellent" or "Good and Very

Good") are associated with negative effects on enrollment rates, suggesting that improved health perceptions may reduce the likelihood of seeking Medicaid enrollment. Specifically: Days in bad physical health significantly positively affect enrollment rates, suggesting that poor physical health is a major motivator for Medicaid enrollment. Conversely, "Overall Health Very Good or Excellent" has a significant negative impact on enrollment rates, implying that individuals in better health may opt out of enrolling.

Second Stage Regression Results with control

Table .7 includes age as a control in the second-stage analysis, which helps control for differences in the age distribution across states.

- Effect of Health Outcomes: When age is included as a control, some of the previously significant effects are no longer statistically significant. This suggests that age may play a confounding role in influencing both health outcomes and enrollment decisions.The inclusion of age reduces the magnitude of coefficients such as "Days in Bad Mental Health" and "Overall Health Very Good or Excellent," indicating that part of the effect of health outcomes on enrollment rates may be age-dependent. In this model, "Overall Health Very Good, Good or Excellent" remains significant at the 5% level, which suggests that individuals reporting better health are less likely to enroll, even after accounting for age differences.

- Effect of Age: Age itself has a positive effect on enrollment rates for most health outcomes, indicating that older individuals are more likely to enroll in Medicaid.

The causal effect tables provide estimates of the relationship between predicted health outcomes and enrollment outcomes, emphasizing the direction and strength of these relationships.

Without Age: The results indicate significant positive causal effects for poor health outcomes like "Days Not in Good Physical Health" on enrollment. For example, each additional

Instruments	Causal Effect	P-value
Days not in good physical Health in past month	0.027	Almost 0
Days not in good mental Health in past month	0.035	Almost 0
Overall Health Very Good Excellent	-0.762	Almost 0
Overall Health Very Good Good or Excellent	-0.490	Almost 0
Overall Health Very Good, Good Excellent and Fair	-0.787	Almost 0
Overall BMI	0.072	0
BMI ≥ 30	0.358	0

Table 2: Causal Effect and P-value in Second Stage(without age variable)

Instruments	Causal Effect	P-value
Days not in good physical Health in past month	0.05	0.0004
Days not in good mental Health in past month	-0.02	0.35
Overall Health Very Good Excellent	0.87	0.35
Overall Health Very Good Good or Excellent	0.37	0.24
Overall Health Very Good, Good Excellent and Fair	0.503	0.04
Overall BMI	0.05	0.02
BMI ≥ 30	-0.18	0.09

Table 3: Causal Effect and P-value in Second Stage(with age variable)

day not in good physical health has an estimated causal effect of 0.027 on enrollment, with a p-value close to zero, implying a highly significant relationship.

With Age: Including age as a covariate generally reduces the strength of these effects, and some relationships become non-significant. For instance, "Days Not in Good Mental Health" has a causal effect of -0.02, with a p-value of 0.35, indicating that after controlling for age, the effect is no longer significant.

5.3 Robustness check

Placebo Effects of the Medicaid Expansion		
Instruments	**LATE**	**P-value**
Days not in good physical Health in past month	2.01	0.53
Overall Health Very Good, Good Excellent and Fair	-0.48	0.12

	Effects of the Medicaid Expansion with lead years		
Year	**Instruments**	**LATE**	**P-value**
2011	Days not in good physical Health in past month	-0.34	0.06
	Overall Health Very Good, Good Excellent and Fair	-0.28	0.14
2012	Days not in good physical Health in past month	-0.29	0.03
	Overall Health Very Good, Good Excellent and Fair	-0.21	0.07
2013	Days not in good physical Health in past month	-0.32	0.02
	Overall Health Very Good, Good Excellent and Fair	-0.23	0.06

Placebo Effects of the Medicaid Expansion

The placebo analysis, as presented in the first table, examines the effects of Medicaid expansion for periods where no actual reform was implemented. This is a critical step to ensure that any observed changes in enrollment rates are genuinely attributable to the Medicaid expansion, rather than reflecting pre-existing trends or unrelated factors.

1. Days Not in Good Physical Health (LATE = 2.01, p-value = 0.53):

2. The p-value of 0.53 is quite high, suggesting that the effect of Medicaid expansion (in this placebo scenario) on the days not in good physical health is not statistically significant. This is an expected outcome in the placebo setting, as the non-expansion states did not actually implement Medicaid expansion.

3. The high p-value indicates that there was no observable effect on physical health in states that did not receive the expansion, providing reassurance that the original observed effects are likely due to the genuine Medicaid expansion, rather than other confounding factors.

   Overall Health Very Good, Good, Excellent and Fair (LATE = -0.48, p-value = 0.12):

4. The LATE for overall health is -0.48, which suggests a potential negative effect in non-expansion states if they were to receive Medicaid expansion. However, the p-value is 0.12, indicating that this effect is not statistically significant.

5. This non-significant effect further supports the credibility of the Medicaid expansion as a valid treatment in the original analysis. The lack of significant changes in health outcomes in non-expansion states in this placebo scenario suggests that the true changes in expansion states are more likely a direct result of the Medicaid expansion itself..

Impact on Enrollment Rates: Implications from Placebo Test

The results from the placebo test provide important evidence regarding the causal effect of Medicaid expansion on enrollment rates:

1. Placebo Effects on Enrollment:

2. Since control states did not experience significant changes in health outcomes when treated as though they had undergone Medicaid expansion, we can reasonably infer that the actual observed changes in the true expansion states are due to the Medicaid expansion.

3. The fact that we do not observe a significant change in enrollment rates during the placebo scenario provides reassurance that the observed increase in actual Medicaid expansion states is not driven by broader time trends or confounding variables that equally affect both expansion and non-expansion states.

4. Supporting the Causal Argument:

5. The lack of significant placebo effects provides strong support for the causal interpretation that Medicaid expansion directly impacted enrollment rates. Specifically, the p-values for the placebo effects are sufficiently high, implying no significant effect in control states that were treated as if they received Medicaid expansion.

6. In the actual treatment scenario, we observed significant effects on enrollment rates, suggesting a robust causal relationship. In contrast, the placebo results, with no significant effects, serve as a falsification test that strengthens the confidence in our findings.

5.4 Discussion

- *Non-Significant DiD Coefficients*:

  In the first stage, the lack of significance in several DiD coefficients suggests that there are likely underlying differences between treated and control states that are not adequately accounted for. These could include unmeasured factors such as changes in health infrastructure or economic conditions that differentially affect states. The non-significant coefficients imply that the impact of Medicaid expansion on certain health outcomes might be less definitive, which limits the robustness of our conclusions. It is essential to consider that without significant effects, we cannot conclusively attribute changes to the policy intervention, and further analyses may need to control for more variables or use different control groups to improve precision.

- *Second Stage Bias: Endogeneity and Instrument Relevance*:

  In the second-stage analysis, we used predicted health outcomes as instruments to assess their effect on enrollment rates. A significant potential bias here lies in the assumption that Medicaid expansion only affects enrollment rates through health outcomes. This assumption may be violated if there are unobserved state-level policies or economic factors that simultaneously influence health and enrollment outcomes. Additionally, while the F-statistics for most instruments in the first stage were above acceptable thresholds, indicating sufficient instrument strength, some lower values suggest a risk of weak instrument bias. Weak instruments can lead to biased estimates, thereby reducing the reliability of the causal interpretation of the second stage. Addressing this issue might involve testing additional instruments or considering alternative modeling techniques.

- *Complexity and Reporting Bias in Health Outcomes*:

  Similar to the first stage, the reliance on self-reported health outcomes adds complexity. The increased access to healthcare may have resulted in heightened awareness of personal health conditions, thereby leading to an increase in the reporting of health issues. This "reporting bias" makes it difficult to differentiate between an actual decline in health status versus an increase in awareness and diagnosis due to improved healthcare access. In the second stage, using these self-reported health measures as predictors of enrollment introduces potential bias. The observed relationships may not accurately reflect the true causal effect, as individuals' perception of health can change independently of their actual health, influenced by access to information and healthcare services.

- *Potential Omitted Variable Bias*:

  In both stages, omitted variable bias remains a critical concern. There may be confounding variables, such as local healthcare initiatives, state-specific economic conditions, or demographic shifts, that simultaneously affect both Medicaid expansion outcomes and enrollment rates. These unmeasured confounders could lead to an overestimation or underestimation of the policy's effects. In future research, including additional covariates such as unemployment rates, healthcare infrastructure quality, and public health campaigns could improve the accuracy of the estimates.

- *Placebo Tests and Robustness Checks*:

  The placebo tests conducted as part of our robustness checks provide important insights into the validity of our model. The lack of significant effects in the placebo tests for certain health outcomes supports the argument that the observed effects in expansion states were indeed due to Medicaid expansion and not due to broader trends. However, the presence of some significant effects in the lead-lag analysis raises concerns about anticipation effects, where individuals or states may have started adjusting their behavior in anticipation of Medicaid expansion. These anticipation effects complicate the interpretation of causal relationships and suggest that the timing of policy implementation must be carefully considered when analyzing policy impacts.

- *Policy Implications and Side Effects*:

  The second-stage results indicate that predicted health outcomes significantly impact enrollment rates. This suggests that Medicaid expansion did not merely provide coverage but also influenced individuals' decisions to enroll based on their perceived and actual health status. However, the analysis also shows unintended side effects: the increase in reported poor health post-expansion may suggest an initial overburdening of the healthcare system or increased diagnosis rates that are not necessarily indicative of a worsening health crisis. Policymakers should be mindful of these potential side effects—such as increased healthcare utilization leading to more diagnoses—which could temporarily paint a negative picture of population health in newly covered groups. Better public health communication may be needed to help individuals understand and adapt to their changing health diagnoses following increased healthcare access.

- *Suggestions for Future Research*:

  Future research should aim to address the limitations of the current analysis by employing richer datasets with more control variables to mitigate omitted variable bias. Additionally, employing other methodologies, such as matching techniques or exploiting other natural experiments, could further strengthen the causal interpretation of Medicaid expansion's effects. Enhancing data granularity by incorporating individual-level data rather than state-level averages may also provide more precise estimates and allow for a better understanding of heterogeneity in treatment effects.

6 Conclusion

The findings demonstrate that Medicaid expansion under the ACA enhanced healthcare access and increased enrollment rates, particularly in treated states. However, variability in results and potential biases, such as reporting bias in self-reported health, highlight the complexities of interpreting health outcome data. Policymakers should address these challenges when evaluating healthcare reforms to ensure accurate assessment and effective implementation. Further research should investigate long-term effects and account for unobservable factors influencing health outcomes and enrollment behavior.

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First Stage: The effect of Medicaid eligibility on Health Outcomes

	Outcome Variables							
	Health Outcomes			Self-Reported Health			Body Mass Index	
	Access to Healthcare	Days in bad Physical Health in Past Month	Days in bad Mental Health in Past Month	Overall Health Excellent or Very Good	Overall Health Excellent Good and Very Good	Overall Health Excellent Good,Very Good and Fair	BMI	BMI ≥ 30
Treatment	0.076***	−0.003	−0.218	0.006	0.016	0.021*	−0.201**	0.035
	(0.028)	(0.380)	(0.470)	(0.014)	(0.019)		(0.100)	(0.111) (0.038)
Pre-Post	0.148***	0.896***	0.278	−0.030***	−0.028**	-0.005	0.532***	−0.012
	(0.010)	(0.196)	(0.191)	(0.007)	(0.012)	(0.009)	(0.124)	(0.014)
DiD	0.019	0.628**	0.658**	−0.006	−0.034**	−0.021**	0.029	0.011
	(0.019)	(0.289)	(0.314)	(0.010)	(0.014)	(0.01)	(0.164)	(0.022)
Constant	0.645***	12.649***	14.531***	0.198***	0.509***	0.814***	27.857***	0.167***
	(0.022)	(0.311)	(0.345)	(0.012)	(0.017)	(0.008)	(0.047)	(0.031)
Observations	761	761	761	761	761	761	761	761
R^2	0.343	0.079	0.024	0.043	0.055	0.046	0.094	0.020
Adjusted R^2	0.341	0.076	0.020	0.039	0.051	0.043	0.091	0.016
Residual Std. Error(df=757)	1.058	17.565	19.009	0.636	0.859	0.562	7.391	1.428
F Statistic(df=3; 757)	132.004***	21.716***	6.202***	11.235***	14.722***	12.286**	26.321***	5.106***

Note: Heteroskedasticity standard errors are used *p<0.1; **p<0.05; ***p<0.01

Table .4: DiD Regression Results(without covariate)

	Outcome Variables							
	Health Outcomes			Self-Reported Health			Body Mass Index	
	Access to Healthcare	Days in bad Physical Health in Past Month	Days in bad Mental Health in Past Month	Overall Health Excellent or Very Good	Overall Health Excellent Good and Very Good	Overall Health Excellent Good,Very Good and Fair	BMI	BMI ≥ 30
Treatment	0.077***	0.009	−0.209	0.006	0.015	0.02**	−0.198*	0.036
	(0.028)	(0.331)	(0.433)	(0.012)	(0.016)	0.01	(0.102)	(0.036)
Pre-Post	0.131***	−0.006	−0.402*	0.003	0.021	0.018*	0.265***	−0.044***
	(0.009)	(0.237)	(0.222)	(0.01)	(0.016)	0.01	(0.1)	(0.017)
DiD	0.019	0.618**	0.651**	−0.005	−0.033**	−0.021	0.029	0.011
	(0.018)	(0.294)	(0.316)	(0.009)	(0.014)	(0.01)	(0.164)	(0.022)
Age	0.004**	0.223	0.168**	−0.008**	−0.012**	−0.006**	0.006***	0.008***
	(0.002)	(0.032)	(0.034)	(0.001)	(0.002)	(0.001)	(0.009)	(0.004)
Constant	0.478***	3.822***	7.871***	0.520***	0.990***	1.036***	25.246***	−0.149
	(0.073)	(1.334)	(1.442)	(0.063)	(0.074)	(0.041)	(0.362)	(0.147)
Observations	761	761	761	761	761	761	761	761
R^2	0.354	0.225	0.099	0.196	0.24	0.139	0.165	0.05
Adjusted R^2	0.35	0.221	0.094	0.192	0.236	0.135	0.161	0.045
Residual Std. Error(df=756)	1.051	16.127	18.275	0.584	0.771	0.534	7.101	1.407
F Statistic(df=3; 757)	103.409***	54.834***	20.775***	46.045***	59.803***	30.56***	37.422***	9.942***

Note: Heteroskedasticity standard errors are used *p<0.1; **p<0.05; ***p<0.01

Table .5: DiD Regression Results(with age)

Second Stage: The effect of predicted health outcomes on enrollment

	Predicted Health Outcomes							
	Health Outcomes			Self-Reported Health			Body Mass Index	
	Access to Healthcare	Days in bad Physical Health in Past Month	Days in bad Mental Health in Past Month	Overall Health Excellent or Very Good	Overall Health Excellent Good and Very Good	Overall Health Excellent Good,Very Good and Fair	BMI	BMI ≥ 30
Enrollment Rates	0.250***	0.040***	0.060***	−1.504***	−0.877***	-0.75**	0.075***	0.045***
(Outcome)	(0.070)	(0.005)	(0.012)	(0.230)	(0.181)	(0.595)	(0.018)	(0.391)
Constant	0.743***	0.404***	0.051	1.217***	1.375***	1.537***	−1.161**	0.913***
	(0.055)	(0.076)	(0.176)	(0.041)	(0.089)	(0.491)	(0.499)	(0.075)
Observations	761	761	761	761	761	761	761	761
R^2	0.064	0.075	0.056	0.071	0.059	0.015	0.056	0.0001
Adjusted R^2	0.063	0.074	0.055	0.070	0.058	0.014	0.054	−0.001
Residual Std. Error	0.731	0.727	0.735	0.729	0.733	0.75	0.735	0.756
F Statistic	52.020***	61.886***	44.871***	58.137***	47.751***	11.499***	44.794***	0.109

Note: Heteroskedasticity standard errors are used — *p<0.1; **p<0.05; ***p<0.01

Table .6: Second Stage Regression Results(without age)

	Predicted Health Outcomes							
	Health Outcomes			Self-Reported Health			Body Mass Index	
	Access to Healthcare	Days in bad Physical Health in Past Month	Days in bad Mental Health in Past Month	Overall Health Excellent or Very Good	Overall Health Excellent Good and Very Good	Overall Health Excellent Good,Very Good and Fair	BMI	BMI ≥ 30
Enrollment Rates	0.172**	0.051***	-0.017	0.870	0.369	0.503**	0.045	−0.181
(Outcome)	(0.084)	(0.013)	(0.044)	(3.178)	(0.885)	(0.827)	(0.048)	(0.307)
Age	0.004**	−0.006	0.009	0.013	0.011	0.009***	0.013	0.007***
	(0.002)	(0.004)	(0.008)	(0.026)	(0.011)	(0.005)	(0.005)	(0.002)
Constant	0.624***	0.508***	0.803***	0.211	0.3	0.146	−0.438	0.657***
	(0.083)	(0.077)	(0.340)	(1.680)	(0.898)	(0.873)	(1.166)	(0.082)
Observations	761	761	761	761	761	761	761	761
R^2	0.109	0.101	0.088	0.088	0.088	0.091	0.094	0.090
Adjusted R^2	0.107	0.099	0.085	0.085	0.086	0.089	0.091	0.087
Residual Std. Error(df = 758)	0.714	0.717	0.723	0.723	0.722	0.721	0.72	0.722
F Statistic	46.541***	42.808***	36.402***	36.407***	36.704***	38.133**	39.206***	37.436***

Note: Heteroskedasticity standard errors are used — *p<0.1; **p<0.05; ***p<0.01

Table .7: Second Stage Regression Results(with age)