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

ECON191 Topics in Economics, UC Berkeley

Minjae Seo

December 27, 2024

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

---

[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.

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.

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:

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

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 2018, 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. 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.

```python
# 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 the ACA, the average age increased slightly to 43.91 years in the Expansion states and 43.71 years in the 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

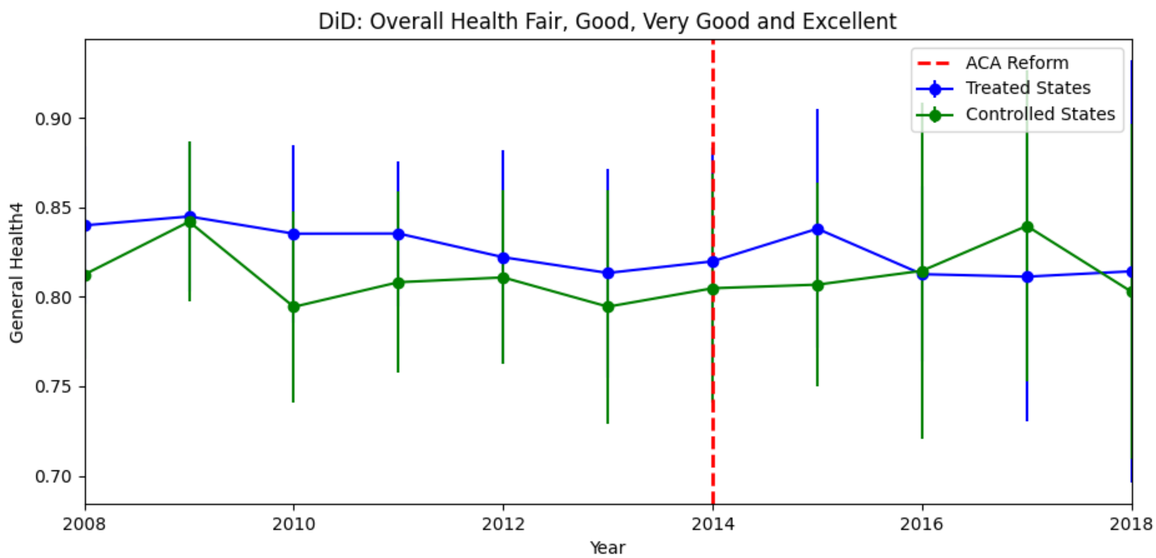
```
for (i in seq_along(first_stage_formulas)) {
  model <- lm(first_stage_formulas[[i]], data = clean, weights = clean$records)
  first_stage_models[[i]] <- model
  clean[[paste0("predicted_health_", i)]] <- predict(model)
}
cat("Predicted days in bad physical days")
cat("\n")
print(head(clean$predicted_health_2))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

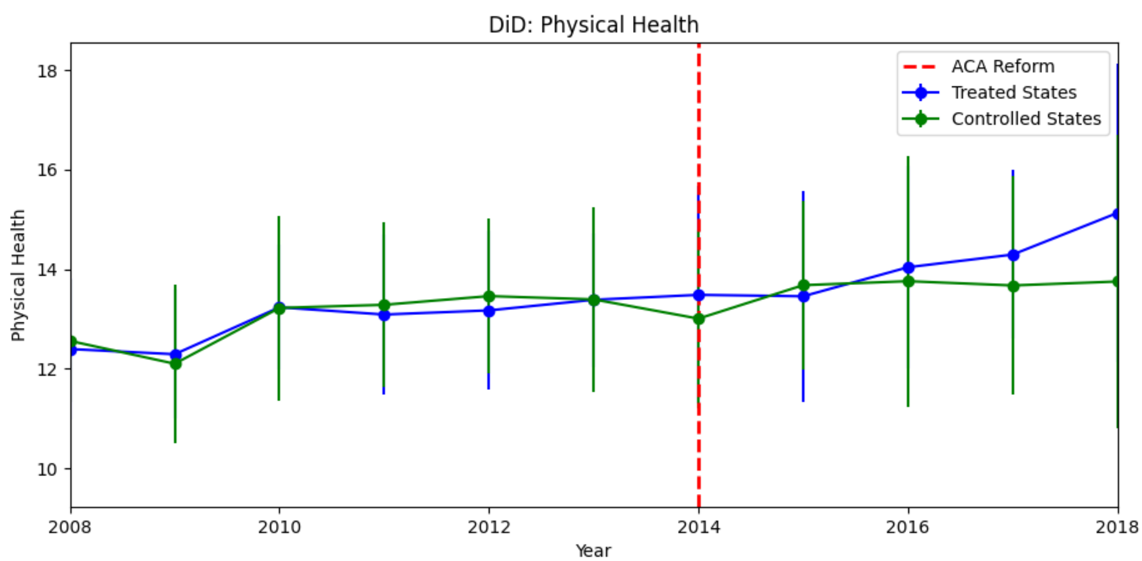
```
Predicted days in bad physical days
       1        2        3        4        5        6
12.05574 12.06432 12.06432 12.06432 12.06432 12.06432

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, and mental health, an Indicator of Obesity(BMI ≥ 30), and an indicator of general health with a scale of 5 from poor to excellent. In the Second Stage, based on using the "predict" command of R, we will estimate the the impact of following predicted health outcomes on enrollment rates and a 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 recording for one unique state with a corresponding year there are a lot of different records, therefore we will adjust the weight by the records of that specific value.

5.1 DiD plot & First Stage





- **Top Plot (Self-Reported Health):** Treated and control states followed parallel trends before the ACA, supporting the parallel trends assumption. After the ACA, the proportion of individuals reporting "excellent, very good, good, fair" health declined in both groups, but the decline was less pronounced in treated states. This suggests that Medicaid expansion may have mitigated the deterioration of self-reported health. However, substantial overlap in error bars indicates high variability, limiting the confidence in detecting a significant treatment effect.

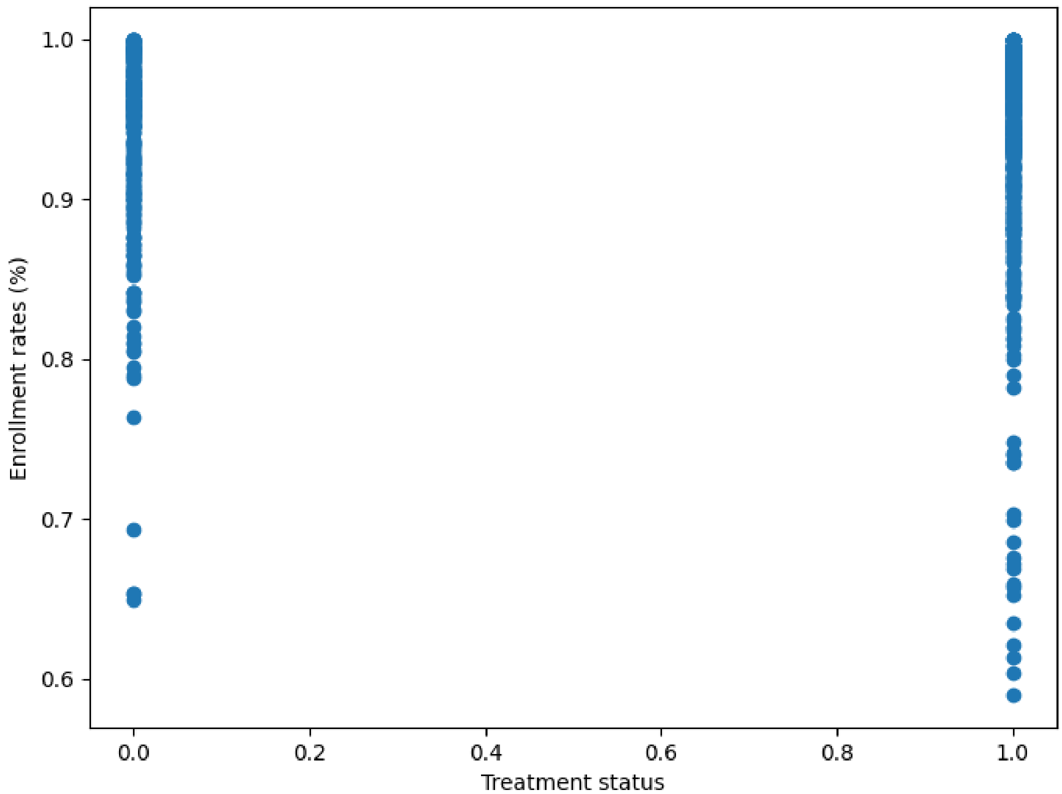
- **Bottom Plot (Days of Poor Physical Health):** Pre-ACA, treated and control states showed parallel trends, validating the DiD model. Post-ACA, treated states initially saw a decrease in poor physical health days, suggesting a positive impact of Medicaid expansion. However, this trend reversed by 2016, potentially due to delayed effects of healthcare improvements or state-specific factors. Overlapping error bars again highlight variability and uncertainty in the precision of the treatment effect.

1. **Relevance Assumption**

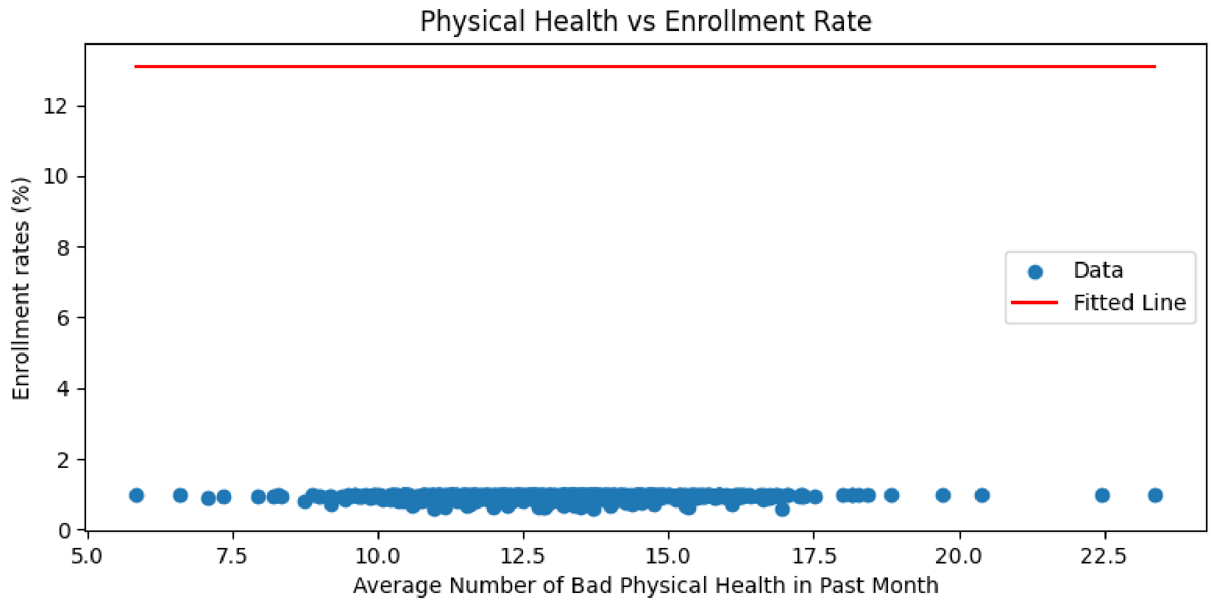
   The relevance assumption is confirmed by examining the F statistics for each health outcome presented in Table .4, .5. The F-statistics range from 5.106 to 132.004, and many are highly significant at the 1% level (indicated by ***). This shows that Medicaid eligibility is strongly correlated with health 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.

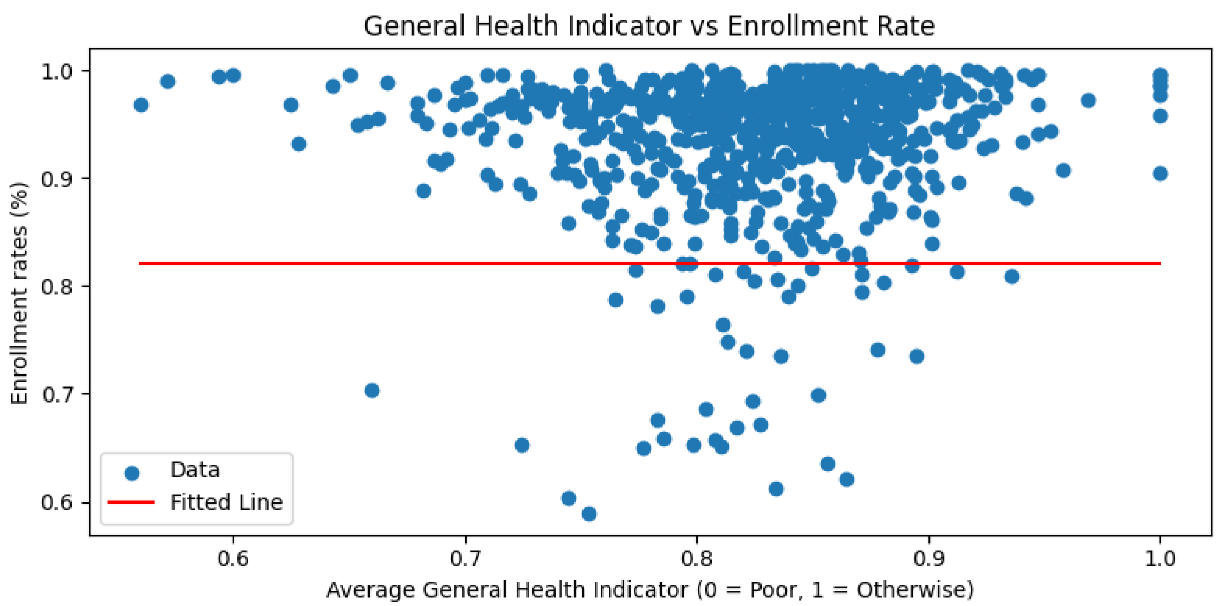
2. **Exclusion Restriction**

   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.

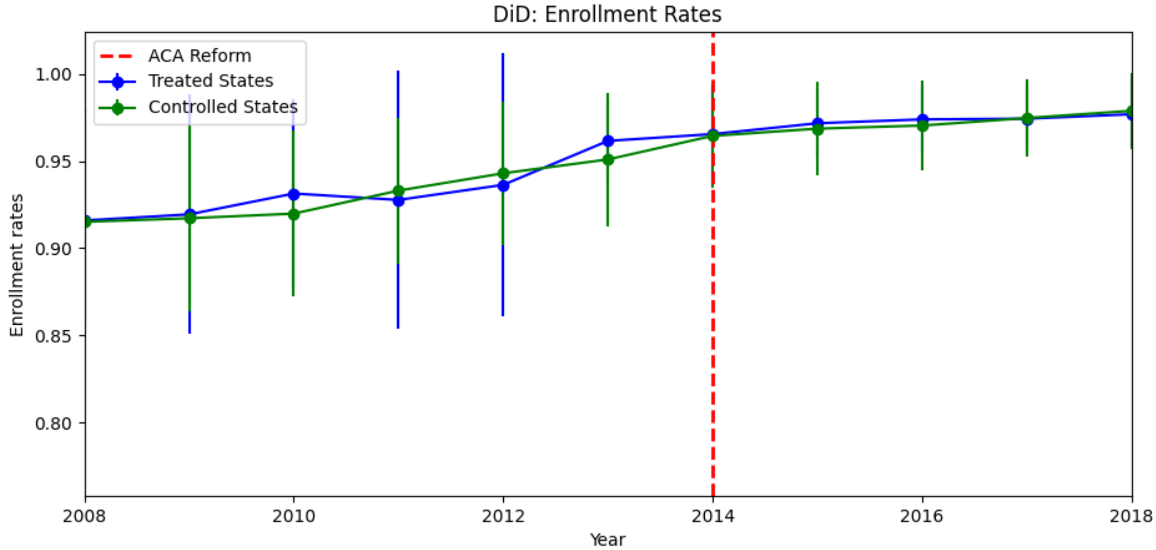


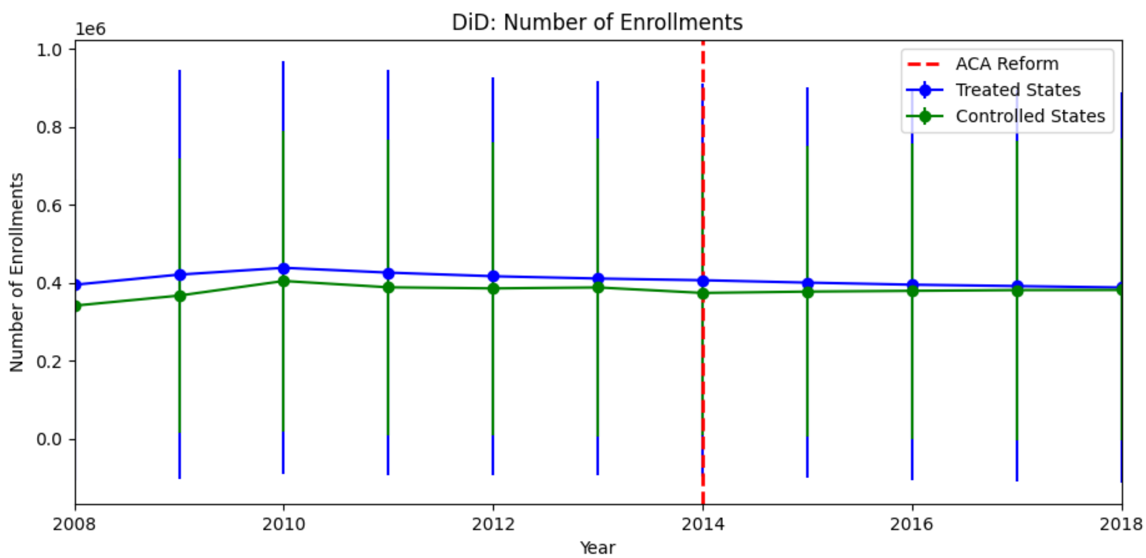
By looking at the scatter plot above and table .6 and .7, we can defend our exclusion restriction assumption that the Medicaid eligibility increases only affect the enrollment rates through health outcomes. Moreover, the two scatters plot below shows the scatter plots and fitted line of each health outcomes. The two scatter plots' fitted line showed the downward trend however we will delve more into our second stage to estimate the local average treatment effect and p-value.


Physical Health vs Enrollment Rate
Enrollment rates (%)
Average Number of Bad Physical Health in Past Month
Data
Fitted Line
0
2
4
6
8
10
12
5.0
7.5
10.0
12.5
15.0
17.5
20.0
22.5


General Health Indicator vs Enrollment Rate
Enrollment rates (%)
Average General Health Indicator (0 = Poor, 1 = Otherwise)
Data
Fitted Line
0.6
0.7
0.8
0.9
1.0
0.6
0.7
0.8
0.9
1.0

5.2 DiD plot &Second Stage





Enrollment Rates:

- *Trends Pre- and Post-ACA:* Both treated and control states exhibited upward trends in enrollment rates before and after the ACA. The parallel trends before implementation support the validity of the parallel trends assumption.

- *Effect Post-ACA:* Treated states showed a marginal increase in enrollment rates relative to controls. However, overlapping error bars highlight significant variability, limiting the precision of treatment effect estimates.

Number of Enrollments:

- *Trends Pre- and Post-ACA:* The trends for the number of enrollments remained consistent between treated and control groups, with no significant divergence post-ACA.
- *Effect Post-ACA:* Observed increases in enrollments were similar for both groups, suggesting minimal additional effects attributable to Medicaid expansion.

Second Stage Regression Results:

Without Age as a Control: Table .6 highlights the impact of predicted health outcomes on enrollment rates:

- *Enrollment Rates:* Poor health outcomes, such as more days in bad physical health, significantly increased Medicaid enrollment rates, indicating that poor physical health motivates enrollment. Conversely, better self-reported health ("Overall Health Very Good or Excellent") negatively influenced enrollment rates, suggesting that healthier individuals may opt out of Medicaid enrollment.

With Age as a Control: Table .7 incorporates age to control for potential confounding effects:

- *Effect of Health Outcomes:* Including age reduced the magnitude and significance of several coefficients. For instance, "Days in Bad Mental Health" and "Overall Health Very Good or Excellent" lost significance, implying that age partially explains their effects on enrollment.
- *Robust Predictors:* "Days in Bad Physical Health" and "Overall Health Very Good, Good or Excellent" remained significant, indicating their strong association with enrollment rates, even after accounting for age.

- *Effect of Age:* Age exhibited a positive and significant effect across most models, suggesting 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.

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)

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 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

5.3.1 Placebo Effects of the Medicaid Expansion

The placebo analysis tests the robustness of our findings by treating control states as if they had implemented Medicaid expansion. The results are shown in the first table, examining whether the instruments Days Not in Good Physical Health and Overall Health Very Good, Good, Excellent, and Fair retain their significance when applied to non-expansion states:

- **Days Not in Good Physical Health (LATE = 2.01, p-value = 0.53):** - The high p-value (0.53) indicates no statistically significant relationship between the instrument and the outcome. This suggests that Medicaid expansion did not have an observable effect on days of bad physical health in the placebo setting. - This non-significant result reassures that the observed effects in the actual treatment states are not driven by confounding factors or unobserved trends that equally affect non-expansion states.

- **Overall Health Very Good, Good, Excellent, and Fair (LATE = -0.48, p-value = 0.12):** - Although the LATE suggests a potential negative effect, the p-value (0.12) indicates that this effect is not statistically significant. This further supports the robustness of the original findings, as placebo-treated states do not exhibit significant changes.

These placebo results reinforce the validity of the Medicaid expansion as a treatment. The instruments, which were significant in the original analysis, lose their significance when applied to non-expansion states, indicating their specificity to the true treatment scenario.

5.3.2 Lead Effects of the Medicaid Expansion

The lead analysis investigates whether the effects of Medicaid expansion are observable in years before its actual implementation. This serves as a falsification test for parallel trends and ensures that no pre-existing differences are confounding the results. The findings across the years 2011 to 2013, presented in the second table, highlight the following:

- **Days Not in Good Physical Health:** In 2011, the LATE is -0.34 (p-value = 0.06), approaching significance but remaining above the 5% threshold. By 2012 and 2013, the effects (-0.29 and -0.32) become more statistically significant (p-values = 0.03 and 0.02, respectively). These findings suggest that pre-treatment differences in physical health were minor but could potentially influence the interpretation of post-treatment results.

- **Overall Health Very Good, Good, Excellent, and Fair:** The LATE remains non-significant in 2011 (p-value = 0.14) and approaches significance in 2012 and 2013 (p-values = 0.07 and 0.06, respectively). While this indicates minor pre-treatment differences, these effects are not strong enough to challenge the validity of the post-treatment findings.

5.3.3 Implications for Enrollment Rates and Causal Inference

The robustness checks provide critical evidence for the validity of the instruments and the causal interpretation of Medicaid expansion effects:

- **Insignificance of Instruments in Placebo Tests:** The two instruments, Days Not in Good Physical Health and Overall Health Very Good, Good, Excellent, and Fair, are not significant in the placebo setting. This confirms their specificity to the treatment scenario, bolstering confidence in their use as valid instruments.

- **Lead-Lag Validation:** While minor pre-treatment differences are observed in lead years, the effects are not sufficiently strong to undermine the main findings. These analyses support the parallel trends assumption, ensuring that the observed post-treatment effects are likely attributable to the Medicaid expansion itself.

5.4 Discussion

- **Non-Significant DiD Coefficients:**

  In the first stage, several non-significant DiD coefficients point to potential unmeasured differences between treated and control states, such as variations in health infrastructure or economic conditions. This limits the robustness of conclusions and highlights the need for more refined models or alternative control groups.

- **Second Stage Bias:**

  The second stage assumes that Medicaid expansion only affects enrollment rates through health outcomes. While most instruments had strong F-statistics, weaker ones suggest potential bias. Exploring additional instruments could reduce this risk in future analyses.

- **Reporting Bias in Health Outcomes:**

  Improved healthcare access may increase the reporting of health issues due to heightened awareness, rather than actual declines in health. This complicates interpreting health measures and their causal relationship with enrollment decisions.

- **Omitted Variable Bias:**

  Confounding factors such as local health initiatives or economic changes may bias results in both stages. Including additional covariates, such as unemployment rates or healthcare infrastructure quality, could improve accuracy.

- **Placebo Tests and Robustness:**

  Placebo tests confirm that observed effects are driven by Medicaid expansion rather than broader trends. However, lead-lag analyses indicate potential anticipation effects, emphasizing the importance of accounting for policy timing in future work.

- **Policy Implications:**

  Medicaid expansion influenced enrollment through health outcomes, demonstrating its broader impact. However, increased reporting of poor health post-expansion may reflect system overburdening or increased diagnoses, not an actual health decline. Policymakers should address these complexities with clear communication and sustained healthcare system support.

6 Conclusion

Since 2014, lower-income households have increasingly adopted Medicaid expansion due to its promise of improved healthcare access and coverage, with the expectation of achieving better health outcomes. However, our analysis reveals several nuanced findings. While

Medicaid expansion significantly improved access to healthcare and increased enrollment rates, it also coincided with unexpected trends in self-reported health outcomes. Specifically, some families reported worse physical health outcomes and a decline in average general health on a five-point scale. These patterns may reflect heightened awareness of health conditions or shifts in healthcare utilization rather than actual declines in health.

Our findings also highlight notable variability across states. For example, days not in good physical health decreased in some states but increased in others, indicating that state-level factors or implementation differences may play a role. Similarly, we found a significant relationship between predicted health outcomes, such as improved healthcare access, and increased enrollment rates, yet these outcomes did not translate into universally improved health perceptions.

While previous research suggests Medicaid expansion eligibility improved academic performance for students in grades 4 through 11, our findings challenge this notion, showing that increased enrollment rates were associated with poorer reported health outcomes. This underscores the complexity of measuring the indirect effects of Medicaid expansion on broader social factors.

The robustness checks, including placebo tests and lead-lag analyses, validated the instrument's strength while revealing variability in health outcomes over time. Notably, our findings suggest that health outcomes and enrollment rates may be influenced by other unobservable factors, such as regional economic conditions or additional state policies.

These results emphasize the need for further research to better understand the interplay between Medicaid expansion, health outcomes, and other social determinants. Future studies should focus on disentangling these effects and ensuring clearer data to provide actionable insights for policymakers.

References

Barbaresco, S., C. J. Courtemanche, and Y. Qi (2015). Impacts of the affordable care act dependent coverage provision on health-related outcomes of young adults. *Journal of health economics 40*, 54–68.

Bullinger, L. R., M. Gopalan, and C. M. Lombardi (2023). Impacts of publicly funded health insurance for adults on children's academic achievement. *Southern economic journal 89*(3), 860–884.

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. P. Newhouse, H. Allen, K. Baicker, and t. Oregon Health Study Group (2012). The oregon health insurance experiment: evidence from the first year. *The Quarterly journal of economics 127*(3), 1057–1106.

Garfield, R., A. Damico, and K. Orgera (2020). The coverage gap: uninsured poor adults in states that do not expand medicaid. *Peterson KFF-Health System Tracker. Disponível em:. Acesso em 29*, 1–11.

Gross, T. and M. J. Notowidigdo (2011). Health insurance and the consumer bankruptcy decision: Evidence from expansions of medicaid. *Journal of public Economics 95*(7-8), 767–778.

Mangan, K. and B. Saloner (2019). The aca's impact on college students. Accessed:2020-07-08.

Miller, S. and L. R. Wherry (2019). The long-term effects of early life medicaid coverage. *Journal of Human Resources 54*(3), 785–824.

Serakos, M. and B. Wolfe (2016). The aca: impacts on health, access, and employment. In *Forum for Health Economics and Policy*, Volume 19, pp. 201–259. De Gruyter.

Simon, K., A. Soni, and J. Cawley (2016). The impact of health insurance on preventive care and health behaviors: evidence from the 2014 aca medicaid expansions. Technical report, National Bureau of Economic Research.

Sommers, B. D., K. Baicker, and A. M. Epstein (2012). Mortality and access to care among adults after state medicaid expansions. *New England Journal of Medicine 367*(11), 1025–1034.

Wehby, G. L., B. W. Domingue, and F. D. Wolinsky (2018). Genetic risks for chronic conditions: Implications for long-term wellbeing. *The Journals of Gerontology: Series A 73*(4), 477–483.

Wherry, L. R. and S. Miller (2016). Early coverage, access, utilization, and health effects associated with the affordable care act medicaid expansions: a quasi-experimental study. *Annals of internal medicine 164*(12), 795–803.

Yeung, R. (2020). The effect of the medicaid expansion on dropout rates. *Journal of school health 90*(10), 745–753.

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)