Impacts of the Medicaid Expansion Under the Affordable Care Act on Health Insurance Coverage

Evan Teal

University of Colorado, Boulder

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Department of Economics

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Advisor: Adam McCloskey, Department of Economics
Counsel Representative: Brian Cadena, Department of Economics
Committee Member: Abram Handler, Department of Information Sciences

Abstract

In this paper, I will look at the impacts of the Medicaid expansion of 2014. In particular: What is the long-run effect of Medicaid Expansion during the ACA on uninsured rates in the United States? I will be utilizing a newer methodology, the difference-in-differences staggered adoption model which allows for multiple time periods. This model proves to be more refined and less biased in comparison to the normal diff-in-diff used in this field. I find that, the Medicaid expansion of 2014 caused an average change in uninsured rates of 2.33 percentage points for states that expanded in comparison to what they would have experienced had they not. This drops to 1.87 percentage points if we allow for one year of anticipation (changes in behaviors of citizens prior to implementation) in our data.

Introduction

Medicaid is a federal and state program that helps with the costs of healthcare for low-income individuals. In this paper, I will focus on the Medicaid Expansion decision of 2014, and will analyze the effects to determine if it was successful in providing better health insurance coverage to American citizens. This expansion was a statewide program, meaning that each state had the option to implement the program. States began to implement in 2014, but there wasn't a universal adoption, with some states waiting a few years before expanding. In 2013, the year before Medicaid Expansion, Medicaid was only eligible for individuals with income up to 64% of the federal poverty level ($7,353.60 for individuals). This expansion offered states the option to increase eligibility for Medicaid individuals to those with incomes up to 138% of the federal poverty level (equating to about $17,000 for a single person). Of course, these incomes vary depending on size of household. Regardless, the expansion allowed for incomes over double what it had previously, effecting a large portion of the population. Relevant literature finds that the implementation of both the Medicaid expansion as well as the full Affordable Care Act decreased the overall uninsured rates in America in states that chose to implement. The overall effect found in the literature varies depending on regression equation, controls, and so on. However — despite variation in results — the trend remains the same, showing a decrease in uninsured rates for states that chose to implement.

My research question is as follows: What is the long-run effect of Medicaid Expansion during the ACA on uninsured rates in the United States? I will be utilizing data from the American Community Survey (ACS). This dataset includes individuals from all 50 states, and shows insurance coverage, age, state poverty levels, etc. I will be using a relatively new methodology, difference-in-differences staggered adoption. This new methodology differs from normal difference-in-differences (DiD) as it considers multiple adoption periods. For example, not all states who implemented Medicaid expansion did so at the same time. Colorado implemented in 2014, Alaska in 2015, Louisiana in 2016, and so on. Using this methodology and allowing for multiple adoption periods will allow for more accurate and less biased results in comparison to a DiD or triple-diff (DDD) model. I will be finding the average treatment effect on the treated (ATT), which is the average effect of some treatment on the group of individuals that were treated. In this paper, the treatment is the Medicaid expansion, and the result will give us the change in uninsured rates from the expansion.

My research contributes to the literature by incorporating a newer and more refined methodology as well as looking at the longer-run effects of the Medicaid expansion by looking at a newer vintage of data. In this paper I will use the new DiD variant which will help remove bias created by not having multiple groups. Further, another contribution relative to the literature is newer data. Much of the literature utilizes data ending from 2014-2016. In this paper, I will use data from 2011-2019 to look at the 6-year effects of the expansion. This contribution might unearth some different results, as it looks at the long run findings, which may vary in magnitude in comparison to the results from previous years. My contributions to the literature will provide us with a less biased understanding of the effects of the Medicaid expansion on uninsured healthcare rates.

Like related literature, this paper finds that the Medicaid expansion decreased uninsured rates. Overall, I see a 2.33 percentage point decrease in uninsured rate for states that chose to implement the Medicaid expansion compared to what they would have experienced had they not expanded. If we account for anticipation, this number falls slightly to 1.87 percentage points. This number is lower than common in the field, with the two most related papers finding a 5 and 3.2 percentage point decrease respectively (Courtemanche et al., Sommers et al.). I will touch on this discrepancy later in the paper.

Literature Review

Although gains in insurance coverage after the Affordable Care Act have been well documented, there appears to be minimal research in this literature which utilize more recent data, as well as the new DiD staggered adoption methodology. The research in this paper on the effects of Medicaid expansion on uninsured rates relates to a wider literature on the effects of the ACA on different medical and healthcare classifications (Casswell et al., 2014; Courtemanche et al., 2017). Casswell et al.(2014) delves into the impact of the ACA on the financial out of pocket medical burden families face in each state. The findings show significant variation in the financial burden of medical spending across states. However, it finds that Medicaid expansion can play a pivotal role in expanding access to medical care at minimal to no cost to low-income individuals. Courtemanche et al.(2017) aims to find the early effects of the ACA on health care access. This study finds that the ACA improved access to care among all dimensions. Health insurance coverage increased by 8.3 percentage points and cost barriers fell 5.1 percentage points. Further, the probability of having an annual checkup went up 3.6 percentage points and having a primary care doctor increased by 3.1 percentage points. These findings were observed in both expansion and non-expansion states. A more specific literature focuses on what factors explain the reduction in the uninsured rates due to the ACA (Frean et al., 2016). This research finds that roughly 40 percent of the ACA's reduction in uninsured rates were attributable to the creation of premium subsidies.

Two more closely related papers to my research involve finding the change in uninsured healthcare rates due to Medicaid Expansion (Sommers et al., 2012; Kaestner et al., 2017). Sommers et al.(2012) digs into the changes in mortality and access to care among adults due to the state Medicaid expansions. This paper finds a relative reduction in mortality of 6.1 percent as well as a 3.2 percent decrease in the uninsured rate. Kaestner et al.(2017) follows the effects of the Medicaid expansion on health insurance coverage and labor supply. The result was that there was a 3-5 percentage point decrease in the uninsured rate for parents and a 4-5 percentage point decrease for childless adults. These numbers vary due to the time period, data source, controls, and fixed effects used. It was further concluded that there was a small and not statistically significant effect of the Medicaid expansion on the labor supply, concluding there was little evidence to show a decrease in work effort. The most closely related paper looks at the three-year impact of the ACA on disparities in insurance coverage (Courtemanche et al., 2018). Some key findings include a decrease in the disparity between the highest and lowest income brackets uninsured rate by 14.1 percentage points, decreased disparity between Hispanic and non-Hispanic uninsured rates by 3.8 percentage points, and a decrease in the disparity between gender by 1 percentage point. The result that is most similar to the analysis in this paper is as follows: a 5 percentage point increase in insurance coverage due to the Medicaid expansion, and an 8.7 percentage point increase due to the full ACA.

My research contributes to the literature by utilizing a newer and more accurate methodology as well as looking at the longer-run effects of the Medicaid expansion by looking at newer vintage of data. Kaestner (2017), Sommers (2012), and Casswell (2014) utilize a difference-in-differences (DiD) methodology in their research. By incorporating the staggered adoption version of DiD into this paper, it allows for less biased results in comparison to the normal DiD used in the related literature. Courtemanche (2017), Frean (2016), and Courtemanche (2018) use a difference-in-difference-in-differences (DDD) methodology which allows them to look at the differences in the DiD findings for certain subgroups. Like the normal version of DiD, the methodology used in this paper allows for more refined results, due to its ability to use multiple groups and periods. Because the normal version of DiD as well as DDD only allow for two time periods, (before and after treatment) it fails to allow for the staggered nature of Medicaid expansion decisions, with states expanding at different time periods. In this paper I will use the new DiD variant which will help remove bias created by not allowing for multiple time periods. My second contribution relative to the literature is newer data. Much of the literature utilizes data ending from 2014-2016. In this paper I will use data from 2011-2019 to look at the 6-year effects. This contribution might reveal some different results, as it looks at the long run findings, which may vary in magnitude in comparison to the results from previous years. My contributions to the literature will provide us with a more accurate understanding of the effects of the Medicaid expansion on uninsured health rates.

Data

The primary data source in this paper is the American Community Survey (ACS). This survey is administered nationwide, sampling from all 50 states and Washington D.C. The ACS collects responses from roughly 1 percent (3,000,000 citizens) of the US population per annum. Data from this survey is collected at the individual-level, however, I have aggregated it up to the state-level as the Medicaid expansion decision was ultimately left to state legislation. The ACS appears to be the most appealing data source for this paper due to its large number of observations, as well as it's mandatory nature which removes survey response bias found in other surveys and data sources. I restricted the data to include responses from 2011-2019, omitting earlier years due to the original ACA provisions that were enacted in March 2010. Including these provisions might have led to confounded results. Due to the effects of COVID-19, the 2019 vintage of ACS data is the most recent they boast. Also, the effects of COVID-19 could create bias in the results, so even if the data were available, I would likely omit it. There have been 5 states that have expended Medicaid since 2019, including Idaho, Missouri, Nebraska, Utah, and Oklahoma. For this paper, these states will not be dropped, but instead put in the "never-treated" group, since the data used doesn't overlap with any effects of their expansion. The sample is further restricted to individuals aged 19-64, as the ACA was not created to change the coverage for those over 64. The ACS asks individuals questions about their type of healthcare (such as Medicaid, individually purchased, employer sponsored, etc.), however for this paper I am just interested in overall health insurance coverage, so these responses were aggregated up to just “with or without” health insurance.

Table 1 provides pre-treatment means and standard deviations of the uninsured rate by state Medicaid expansion status. States that were never treated had the highest uninsured rate at 18.84%. For states that did expand, it appears that the earlier a state expanded, the lower the uninsured rate they boasted. States that expanded at the first chance in 2014 had a pre-treatment 3.6% uninsured rate, which is about a third the rate of states that expanded in 2019, having a 11.28% rate. These pre-treatment variations are likely determined by other qualities of the states, such as income, political status, poverty levels, and so on.

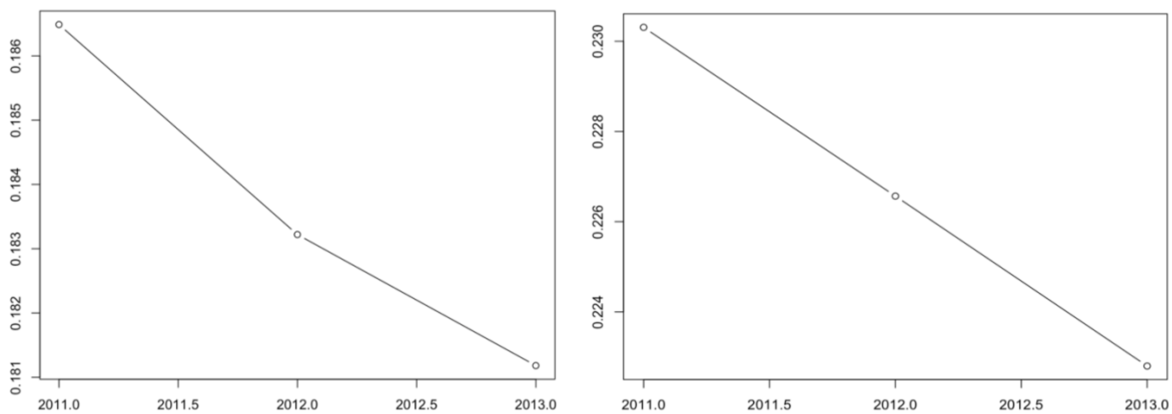
Table 1. Pre-treatment means and standard deviations of dependent variable by state Medicaid expansion status.

	Never Treated	**2014**	**2015**	**2016**	**2019**
Uninsured Rate	0.1884 (0.05291097)	0.0360 (0.05711254)	0.0796 (0.05240710)	0.1176 (0.05782309)	0.1128 (0.02252481)

Note: Standard deviations in parenthesis

Figure 1 presents changes in uninsured rates pre-treatment (2011-2013) by Medicaid expansion decision. Although states that expanded Medicaid always had lower uninsured rates, the overall trends remained constant. It appears that no matter the original insurance rate, when one group goes down, they all go down by similar magnitudes, and vice versa. This finding is crucial for the DiD Staggered Adoption methodology, as it allows us to accept the parallel trends assumption more confidently, since states uninsured rates acted homogeneously to changes over time pre-treatment.

Figure 1. Pre-treatment uninsured rate trends (expanded states on left, never expanded on right)



Methodology

In this paper, I will use a new methodology, the difference-in-differences staggered adoption, who's specification is as follows:

$$\boldsymbol{\widehat{ATT}^{NY}_{OR}(g,t) = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{G_{i,g}}{\frac{1}{n}\sum_{j=1}^{n}(G_{g,j})}\left(Y_{t,i} - Y_{g-1,i} - \widehat{m_{g,t,\iota}}(X_i)\right)\right]}$$

where $\widehat{ATT}^{NY}_{OR}(g,t)$ is the average treatment effect on the treated (states that chose to expand Medicaid) for group g in year t. In this paper, the groups are determined by state Medicaid expansion decisions, so states that never implemented are assigned to g=0, and for states that did expand, g is equal to the year they chose to expand. The letter n represents the number of states, which is 51 in this paper, meaning $\frac{G_{i,g}}{\frac{1}{n}\sum_{j=1}^{n}(G_{g,j})}$ is the proportion of states treated at time g. $Y_{t,i}$is the uninsured rate for state i at time t, and $Y_{g-1,i}$ is the uninsured rate for state i at time g-1; the year before they expanded. Finally, $\widehat{m_{g,t,i}}(X_i)$ is a regression function for the never treated group. This function predicts how the changes in the uninsured rate (conditional on covariates) would have evolved if the expansion states had not chosen to expand. This means we must accept the identifying assumption of parallel trends, allowing for changes in non-expansion states to be equivalent to changes in expansion states had treatment not happened.

The regression function for the never-treated group is:

$$\boldsymbol{m_{g,t,i}(X_i) = E\left[Y_{t,i} - Y_{g-1,i} | X_i, C_i = 1\right] \approx \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}}$$

where $Y_{t,i} - Y_{g-1,i}$ is the change in uninsured rates from time t to time g-1, conditional on covariates, given the state never expanded Medicaid.

The overall DiD staggered adoption model gives us the change in the uninsured rates from Medicaid expansion compared to what would have happened had the state chose not to expand. Referring to the first equation, for a state that implemented it would find the change in uninsured rates from before to after treatment. Then, utilizing parallel trends, we can assume the function for the never-treated group is the change in uninsured rates that would have happened in the state without expansion. So, by subtracting this from the initial change over time, it shows the true effect of the Medicaid expansion.

Results

In this paper, we will compare different variations of the DiD staggered adoption model, utilizing various covariates and anticipation periods. I will then compare those findings to the normal DiD, which is most common in this field of research. In this section I will just be alluding to the baseline DiD staggered adoption model with no covariates or anticipation. I will touch on the other models in the next section. Table 2 represents the overall effect, which is constituted as a weighted average of all group-time average treatment effects with the weights proportional to group size. This is the overall change in the uninsured rate due to Medicaid expansion using the DiD staggered model with no controls or anticipation. I find a 2.33 percentage point decrease in the uninsured rate for states that chose to expand Medicaid compared to what they would have experienced had they not expanded.

Table 2. Weighted average of all group-time average treatment effects with weights proportional to the group size (baseline model)

	ATT (g,t)	Std. Error	[95% Simult.	Conf. Band]
Full Sample	-0.0233	0.0068	-0.0366	-0.01*

Note: "" confidence band doesn't cover 0*

Table 3 outputs the ATT estimates for each group by years after adoption. Although the estimates vary in magnitude for each group, the overall trend remains the same. The Medicaid expansion leads to an immediate decrease in uninsured rates, which of course is expected. Over time however, the uninsured rate continues to decrease at the 1 year after implementation mark, but remains constant after.

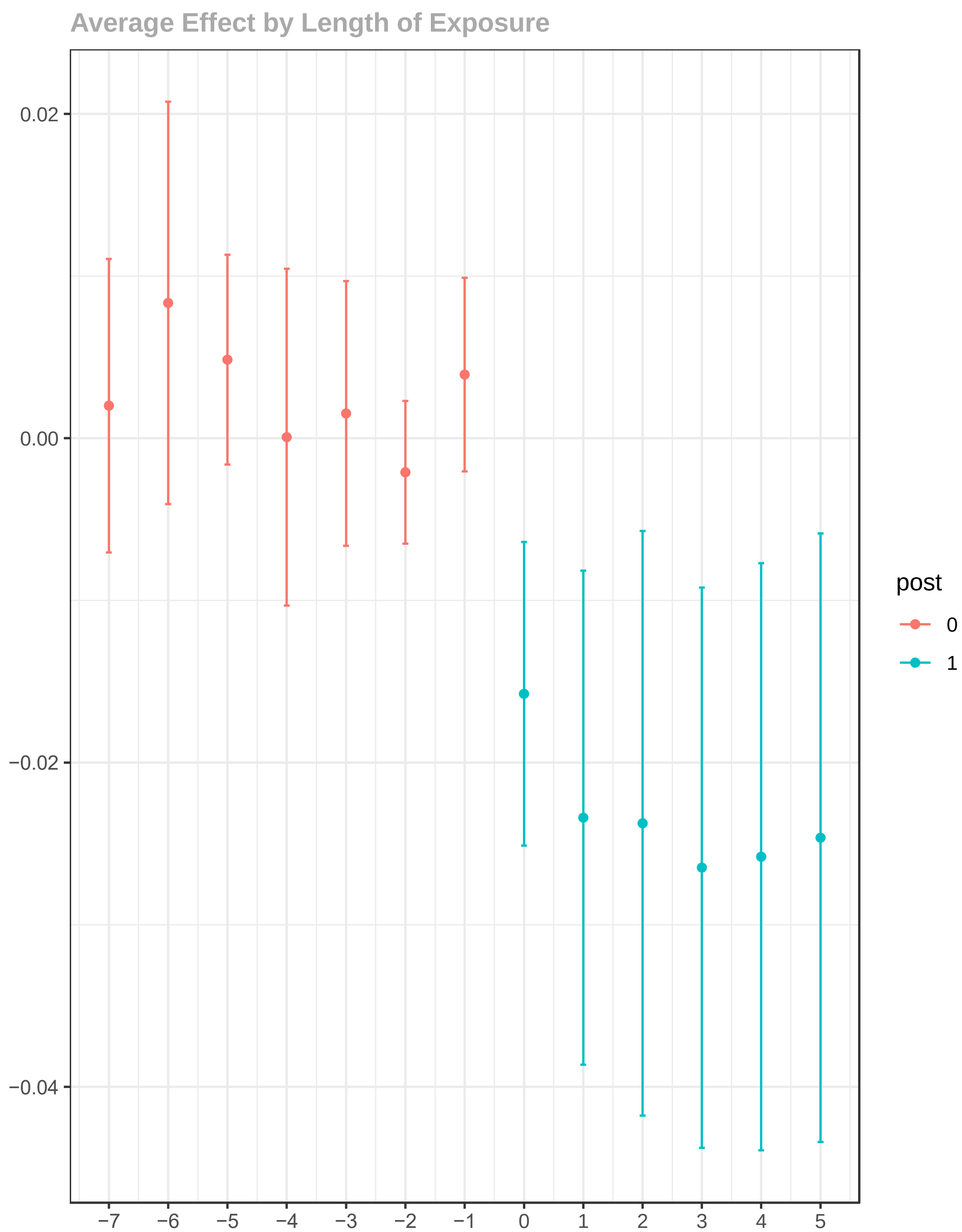
Table 3. ATT estimates for each group by years after adoption (baseline model)

	0	1	2	3	4	5
2014	-0.0162 (0.0045)	-0.0230 (0.0074)	-0.0221 (0.0076)	-0.0245 (0.0076)	-0.0252 (0.0074)	-0.0246 (0.0078)
2015	-0.0104 (0.0040)	-0.0136 (0.0070)	-0.0193 (0.0055)	-0.0273 (0.0056)	-0.0310 (0.0075)	
2016	-0.0258 (0.0065)	-0.0431 (0.0073)	-0.0533 (0.0071)	-0.0520 (0.0033)		
2019	-0.0083 (0.0051)					

Note: standard error in parenthesis

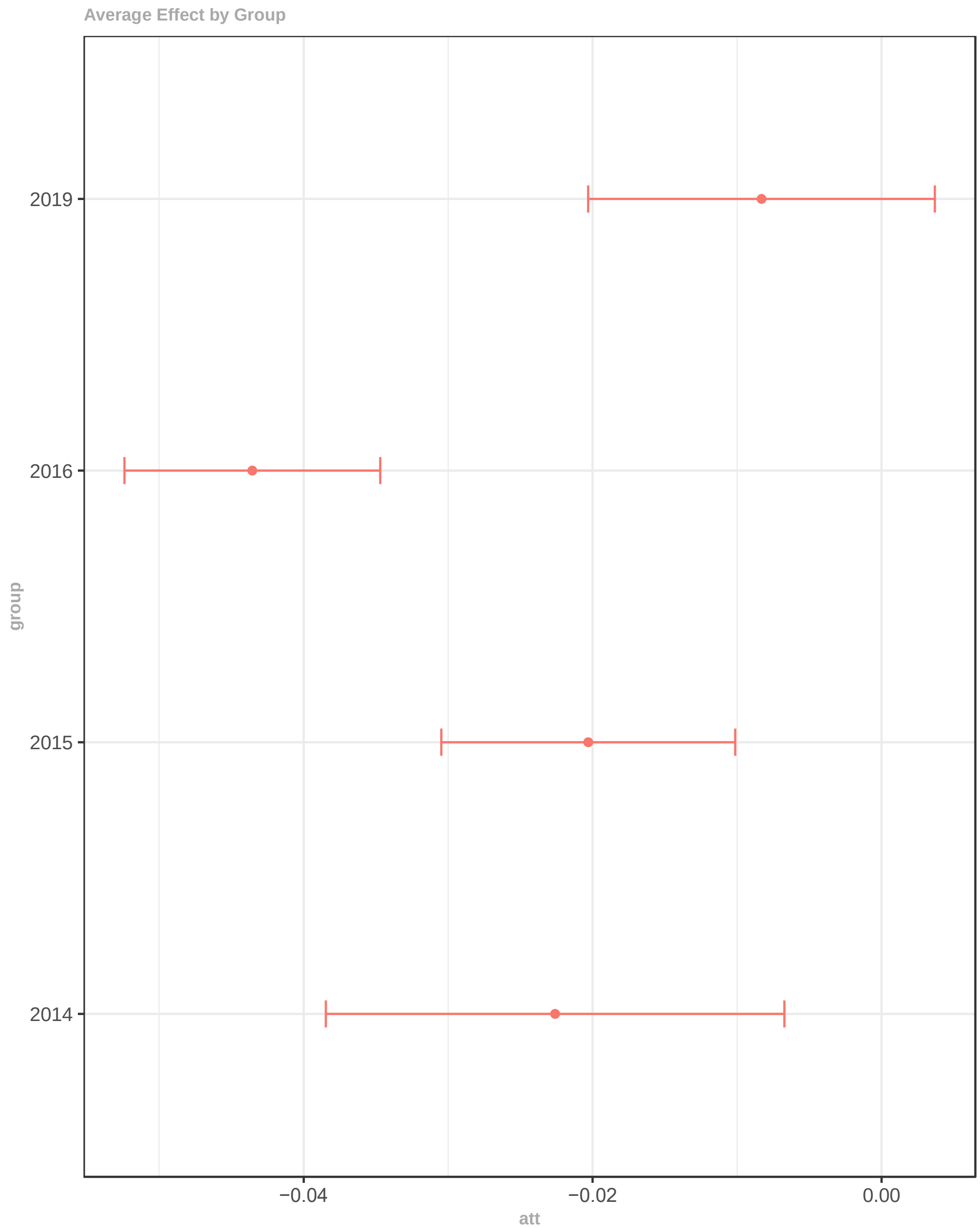
This is shown more clearly in Figure 2. This figure tells us that there are immediate impacts of Medicaid expansion, which leads to a decrease in uninsured rates of about 1.5 percentage points; however, there are some aspects that take about a year to fully implement. After about a year, where we see full implementation of the effects of the expansion, the change in uninsured rates remain relatively constant at about 2.4 percentage points over time. This is an important finding as it shows that the effects of the expansion weren't just short-term impacts, but in fact changes that are homogenous throughout time.

Figure 2. ATT estimates by years after adoption (baseline model)



Now, an important differentiation between this method and the standard diff-in-diff is its utilization of multiple groups. Figure 3 visualizes the ATTs for each group to analyze differences across that dimension. There appears to be a negative relationship between group and the change in uninsured rate, meaning that the later a state implemented, the larger the uninsured rate would decrease. This makes sense as if we turn back to Table 1, we see that the later a state implemented, the higher their pre-treatment uninsured rates were. So, given that these states had higher uninsured rates to begin with, it makes sense that the implementation of the same program would lead to larger changes for them in comparison to states that already had lower rates to begin with. The 2016 group appears to deviate from this relationship, which is most likely explained by the lower number of observations in that group, which causes high variance and noise in the model.

Figure 3. ATT estimates by group (baseline model)



Robustness Check

The method used in this paper allows for both controls/covariates and anticipation periods. To check for robustness, I ran the model with different combinations of each of these variables. To begin, I used poverty rate as well as income (both aggregated to state estimates) as potential determinants of trends. Table 4 shows the overall average ATT from the model utilizing this matrix of covariates. I find a 2.58 percentage point decrease in the uninsured rate for states that expanded Medicaid in comparison to their expected change without expansion, conditional on the covariates. This does not vary much from the 2.33 we had found in the baseline model. Of course, since these are estimates, every time you run the model you will get slightly different results. I can therefore claim that there is no real change in the average treatment effect utilizing covariates, so I conclude that the model is robust to covariates.

Table 4. Weighted average of all group-time average treatment effects with weights proportional to the group size (with covariates)

	ATT (g,t)	Std. Error	[95% Simult.	Conf. Band]
Full Sample	-0.0258	0.006	-0.0375	-0.0141*

Note: "" confidence band doesn't cover 0*

Table 5 provides the ATT estimates for each group, and comparing it to the baseline model, yet again I fail to see enough evidence to say that the model isn't robust to covariates. The slight variation in magnitude of the estimates can mostly be explained by variation in testing.

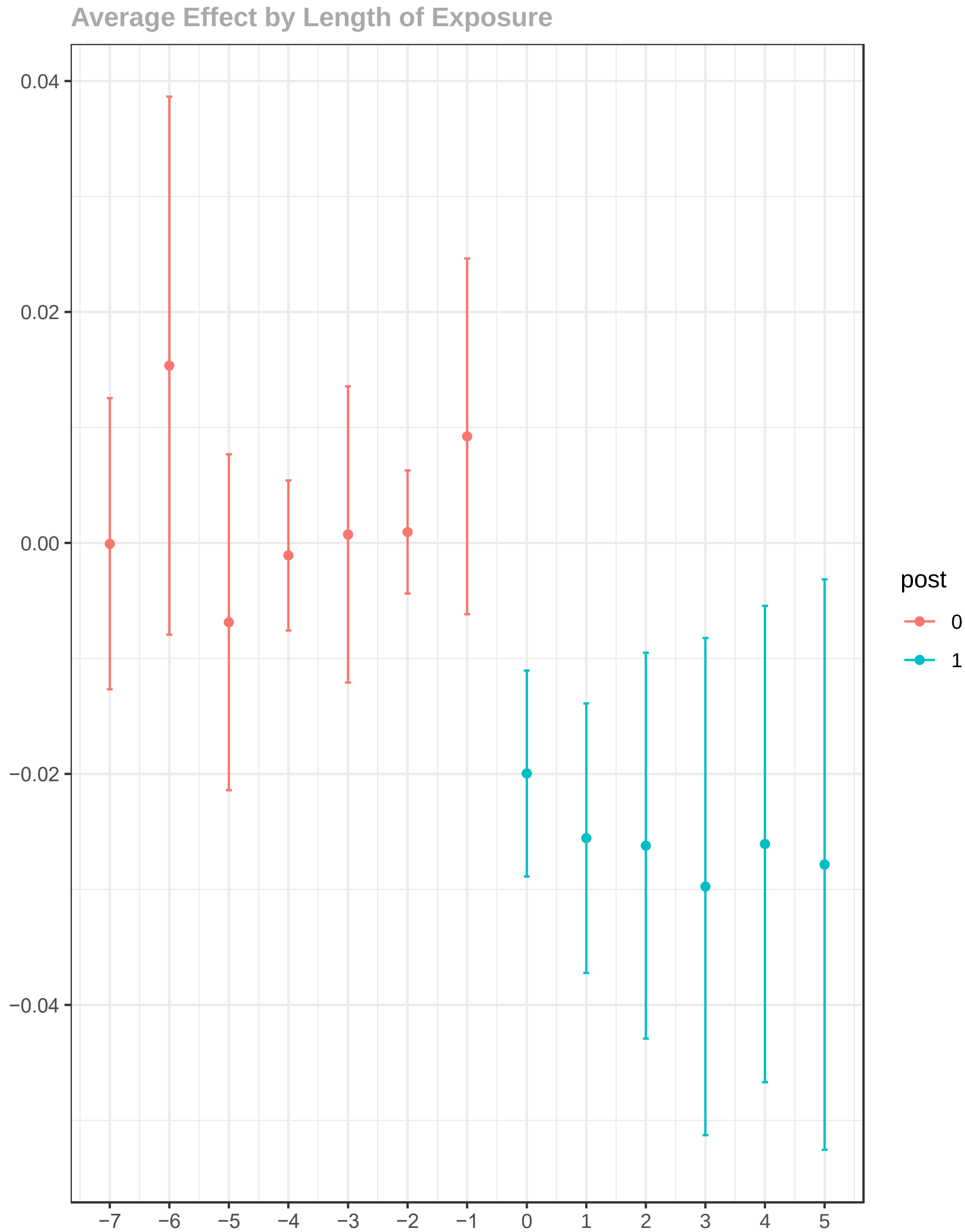
Table 5. ATT estimates for each group by years after adoption (with covariates)

	0	1	2	3	4	5
2014	-0.0214 (0.0049)	-0.0257 (0.0059)	-0.0250 (0.0078)	-0.0288 (0.0098)	-0.0255 (0.0087)	-0.0278 (0.0103)
2015	-0.0113 (0.0021)	-0.0132 (0.0110)	-0.0193 (0.0107)	-0.0240 (0.0101)	-0.0309 (0.0120)	
2016	-0.0244 (0.0067)	-0.0421 (0.0070)	-0.0534 (0.0075)	-0.0513 (0.0046)		
2019	-0.0093 (0.0051)					

Note: standard error in parenthesis

Figure 4 illustrates the effect by length of exposure, and although the estimates are slightly different, the overall trend remains the same to the baseline model. We see a large decrease in the uninsured rate by about 2 percentage points initially, and about one year after expansion we see a 2.5 percentage point decrease which sees little deviation over the following years.

Figure 4. ATT estimates by years after adoption (with covariates)



The second variable of interest in the model is anticipation. Now, anticipation in this model means that there is a change in behavior in anticipation of the treatment. In this paper, I set anticipation equal to 1 year. The use of anticipation imposes conditional parallel trends in pre-treatment years, causing the parallel trends assumption to be stronger as anticipation is increased. This can be important especially if there might be anticipation, and in this paper, it seems acceptable to assume that people were changing their behaviors in anticipation of Medicaid expansion in their state. Table 6 outputs the average ATT with anticipation equal to 1 year. From this, we find a 1.87 percentage point decrease in uninsured rates for states that expanded Medicaid. This is a reasonably large deviation from our baseline model, with a decrease of 0.46 percentage points, or about a 20 percent change.

Table 6. Weighted average of all group-time average treatment effects with weights proportional to the group size (anticipation=1)

	ATT (g,t)	Std. Error	[95% Simult.	Conf. Band]
Full Sample	-0.0187	0.0066	-0.0315	-0.0058*

Note: "" confidence band doesn't cover 0*

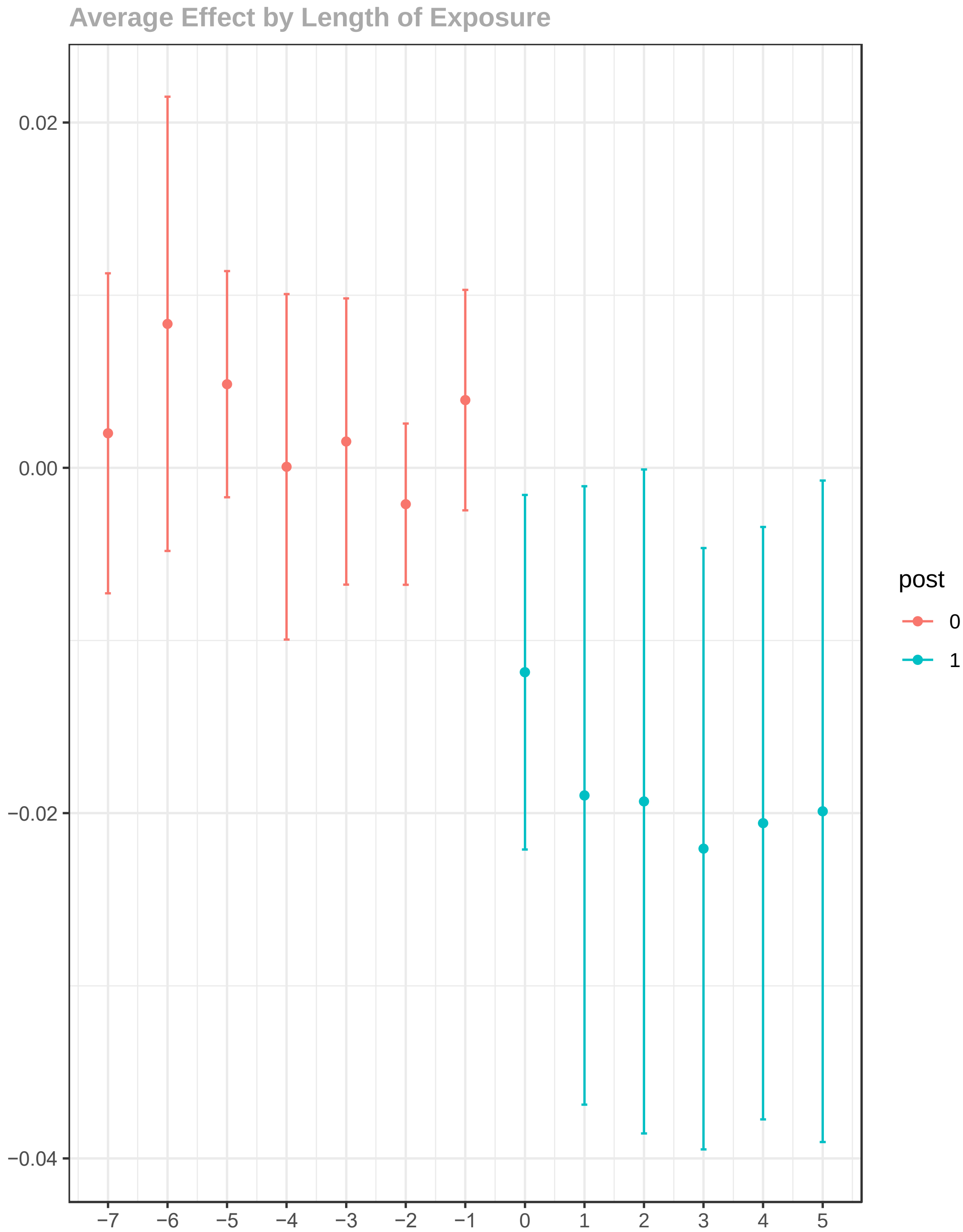
Although this change doesn't affect any of the trends or overall findings of the baseline model, the effect does appear to be heterogenous to the baseline model. This means that the baseline model is not robust to anticipation of 1 year. Now what exactly does this mean? Well, it shows us that there is in fact statistical evidence that people were changing their behaviors about a year before expansion of Medicaid. This would make sense, as people who were not originally included in Medicaid, but would be after expansion, might not purchase insurance because they know they will be covered the following year under Medicaid. This would lead to an artificial increase of the uninsured rates in states that are expanding Medicaid; an increase that is absent in non-expansion states. In doing so, it leads to a bigger discrepancy between pre- and post-treatment uninsured rates, leading to a higher average treatment effect. This treatment effect is positively biased by the anticipation, as the uninsured rate spikes right before expansion due to consumers behavior changes. This causes for the impacts of the expansion to appear larger than they really are. Because the model controls this change, it gives us a smaller change in uninsured rate in comparison to the baseline model, a result that might be more accurate and less biased. Although the baseline, covariate, and anticipation models all vary, the overall trends remain the same, as seen in Table 7 and Figure 5. When controlling for anticipation, there is an initial drop in the uninsured rate at about 1.25 percentage points, and after about a year it levels out to its constant rate of 1.9 percentage points.

Table 7. ATT estimates for each group by years after adoption (anticipation=1)

	0	1	2	3	4	5
2014	-0.0114 (0.0046)	-0.0183 (0.0079)	-0.0173 (0.0086)	-0.0198 (0.0085)	-0.0205 (0.0081)	-0.0199 (0.0078)
2015	-0.0008 (0.0059)	-0.0040 (0.0105)	-0.0097 (0.0087)	-0.0177 (0.0075)	-0.0214 (0.0079)	
2016	-0.0334 (0.0053)	-0.0507 (0.0084)	-0.0609 (0.0085)	-0.0596 (0.0046)		
2019	-0.0123 (0.0049)					

Note: standard error in parenthesis

Figure 5. ATT estimates by years after adoption (anticipation=1)



Comparison to Standard Difference-in-Differences

The most frequent method used in research in this field is the standard difference-in-differences. This methodology compares pre- and post-treatment uninsured rates for states that expanded. It takes this difference and subtracts that from the difference in uninsured rates for the same time span for non-expanded states. This gives us the diff-in-diff, or another words, the effect of Medicaid expansion on uninsured rates. The standard DiD doesn't allow for multiple groups and periods, so I split the data up into different aggregations. First is the not treated group, which is constituted as states that never expanded Medicaid. The treated group was the states that implemented in 2014, and the states that expanded later than 2014 were omitted from the data. The omission of data to utilize this method might cause for skew and bias due to its non-inclusion of the later expanded groups. As we saw earlier in Figure 3, typically a later expanded group experienced a larger decrease in the uninsured rate, which means by omitting these later expanded states, we will most likely see a negatively skewed, lower estimate. This means we will most likely see a change in uninsured rate which is lower than the one we found in Table 2 using the new DiD staggered adoption model.

Below is the regression equation I used for the standard DiD:

$$\boldsymbol{Y_{it} = \beta_0 + \beta_1 Time_t + \beta_2 Medicaid_i + \beta_3 [Time * Medicaid]_{it} + \varepsilon}$$

Where Y is the uninsured rate, β_0 is the baseline average, $Time_t$ is whether year t is after treatment (=1) or pre-treatment (=0). $Medicaid_i$ is whether state i expanded Medicaid (=1) or chose not to implement (=0). The interaction term, $[Time * Medicaid]_{it}$ is the variable of interest, as it is only equal to 1 when a state expanded and the time is post-treatment, or in other words, the change in uninsured rates due to Medicaid expansion. Finally, ε is the standard error term.

Table 8 shows the results from the normal DiD regression. The result I am interested in is the interaction terms coefficient.

Table 8. Effects of Medicaid expansion on uninsured rates (standard DiD)

	Estimate	Std. Error
Intercept	0.226558	0.007496
Medicaid	-0.052968	0.009009
Time	-0.057257	0.009181
Medicaid*Time	-0.018306	0.011034

In this regression, I got a decrease in the uninsured rate by 1.83 percentage points for states that expanded in comparison to what they would have experienced had they not expanded. This result is smaller than the baseline DiD staggered adoption — as expected from my discussion earlier — by 0.5 percentage points. Likely this lower estimate can be explained by the removing of the states that expanded later than 2014. Because these groups had lower uninsured rates pre-treatment, they also saw a higher post-treatment decrease. The larger decrease these states saw was omitted from the standard DiD regression, hence why its treatment effect was smaller. In this case, it seems like the DiD staggered adoption led to less biased and more accurate results due to its inclusion of these key data points that the standard DiD didn't incorporate.

Discussion

From the results above, it can be concluded that the DiD staggered adoption model provides more refined results in comparison to the standard DiD used in the field. Of course, this appears to be solely in the longer run. In this case, the groups that expanded later saw greater decreases in uninsured rates than the initial 2014 group. This might be due to political, economic, or other factors between states that cause for initial, pre-treatment discrepancies in uninsured rates. Since not all groups experience the same change, utilizing the normal DiD will lead to bias and less refined estimates. As mentioned earlier, the higher the pre-treatment uninsured rate in a state, the larger decrease or change they are expected to see post-treatment. This would mean that the group that would benefit the most from Medicaid expansion is the one not using it; the never treated group. These states have political forces pushing them away from adopting this expansion. All the never-treated states are historically Republican oriented. Meanwhile, Medicaid expansion was a provision of the ACA, a program passed by President Barack Obama, a member of the Democratic Party. Given that this program was created by the opposing party, a lot of the never expanded states still are hesitant to implement. This hesitance is only a hindrance to themselves, as these states are expected to see the largest decrease in uninsured rates if expanded.

Now that I have touched on the different versions of the DiD methodology, I will move on to a discussion of just the staggered adoption. Regardless of covariates and anticipation in my model, there is a universal trend which shows us that it took about a year for the full effects of the expansion to implement. Probably the most important finding of this paper was the longevity of the program. Because this is one of the only papers that looks at the Medicaid expansion effects from a more macroscale, it was unknown whether the effects we saw from this expansion were only temporary. The model shows that after one year of implementation, the average treatment effect remains homogeneously fixed at the same magnitude from year to year. Before the implementation of the Medicaid expansion, there was debate as to whether the program would work, and the longevity of it.

One of the main limitations of this paper is the lack of long-term data. At the time of writing this paper, we only have data up to 6 years post expansion, which isn't enough to say for certain this trend will continue. Especially with the large impacts that the COVID-19 pandemic has had on our economy, I think that it might be a few more years before we can truly test this again without having skewed results. However, given my findings I can at least say that for the first 6 years of its implementation, the Medicaid expansion has not only decreased uninsured rates in the states that are treated, but that the magnitude of this effect has remained constant over time. The second main limitation in this paper is the lack of observations in certain groups. During the expansion of Medicaid, most groups fell into either implementing in 2014, or never implementing at all. Granted there are states that chose to implement later than 2014, however the number of these states is smaller than preferred. This lower size of certain groups might lead to high variance and biased results. Optimally, I would have utilized more observations for each group, as well as data further after implementation to give a more complete analysis with lower probability of risk and variance in my results.

In related literature, Courtemanche et al. finds a 5-percentage point decrease in uninsured rates, and Sommers et al. finds a 3.2-percentage point decrease. The first paper utilized DDD, with the latter using standard DiD. Of course, each paper's estimates will vary depending on controls, data, and so on. My results, utilizing the DiD staggered adoption with a one-year anticipation, found a much lower, 1.87 percentage point decrease. In both papers mentioned above, the states that expanded in 2014 were the treated, and every other state was the non-treated. The reason why the results found in this paper are lower than the one in the literature is probably due to the anticipation I mentioned earlier, where when it's not controlled for, will cause higher estimates. This doesn't mean that the other papers estimates are less correct. Instead, it simply means that utilizing the newer methodology which allows us to control for anticipation, I found the treatment effect to be lower than is typically reported in the literature.

Conclusion

With the utilization of the new DiD staggered adoption model, I found that there is a 2.33 percentage point decrease in the uninsured rate for states that expanded compared to if they never did. This model is robust to both income and poverty level. However, there does appear to be evidence that there is one year of anticipation prior to expansion. This is most likely caused by people who were not previously included in Medicaid, who with the new expansion, would be. These people would likely ditch insurance all together in anticipation of their inclusion in Medicaid the following year. This causes for pre-treatment uninsured rates to be higher than typical, causing for a positively skewed, or higher than expected effect post-treatment. This leads to the conclusion that there is a 1.87 percentage point decrease if you control for this anticipation. This estimate shows us that the effects of Medicaid expansion might be lower in magnitude then projected in the literature. However, even if true, it still tells us that the Medicaid expansion of 2014 was effective at its goal of increasing health insurance coverage in America.

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