Affordable Care Act: Studying its Local Impact at Thresholds of Benefit Qualifications

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Abstract

The Affordable Care Act (ACA) is a national health care reform passed by Congress in 2010 and implemented in 2014. Several policies, including the individual health care mandate, subsidies on privately-purchased health care, Medicaid expansion, and the employee's dependent's coverage mandate, has profoundly impact people's choices and financial status. In this paper, regression discontinuity design (RDD) is used to identify any impact occurring locally around the pre-determined benefit threshold. The analysis shows that mandates that impose fine if violated lead to an increase in healthcare coverage rate. Programs that offer a financial incentive are not as effective in encouraging individuals to obtain health care. General costs of out-of-pocket costs rise after the ACA, which contradicts its goal. The results give an insight into the effectiveness of policies in the Act for potential further modification of the act.

1. Introduction

Health care has long been a concern in the U.S. To many Americans, health care expenditure makes up a considerable portion of their income. The health care expenditure has skyrocketed since the 1960s with the health spending increasing from 5% of GDP to 17.4% of GDP in 2013.[1] A large portion of spending from households goes to health care system. Therefore, to those who do not have coverage, a short visit to the hospital can significantly change their spending budget in the following days. At the same time, not every American has health insurance coverage. Since 1999, the private health insurance coverage rate for non-elderly individuals has been constantly declining at a rate of 1.2%-1.8% annually. Although the proportion of the non-elderly population without health coverage has remained at 17%, the number of people increases to 43.3 million in 2007 due to a larger population in these days.[2] Under this context, the Congress passed the Affordable Care Act in 2010 under the push from then-current President Obama, whereas many of the policies were implemented in 2014. The

[1] Data is obtained from "History of Health Spending in the United States, 1960-2013" by Aaron C. Catlin and Cathy A. Cowan. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/HistoricalNHEPaper.pdf

[2] Data are obtained from "Health Insurance Coverage Trends, 1959–2007: Estimates from the National Health Interview Survey" by Cohen, et al. (2009). The article can be found at https://www.cdc.gov/nchs/data/nhsr/nhsr017.pdf

goals of the Affordable Care Act are to expand universal health care coverage and to create easy access to medical service for the population, especially those with lower income (Clemmitt, 2012). To serve these purposes, policy changes including the individual mandate that penalizes uninsured people, subsidizing low income families on private insurance, expanding the scope of coverage of Medicaid, and allowing dependents under 26 to be under parents' employer-sponsored insurance were enacted. Many of these policies are targeted at populations with a lower coverage rate as low-income families usually cannot afford to buy health insurance. Additionally, young adults also have a low coverage rate, with about 30% of young adults between age 19-26 being uninsured (Frerich, et al., 2012),

After the implementation of new health care policy in 2014, certain groups of individuals can receive financial benefits from the reform if they meet the corresponding criteria. One of these groups is individuals with a household income below 400% of Federal Poverty Level (FPL), who receive subsidies.[3] These subsidies are designed to relieve the financial burden of low income families who purchase health insurance plan through the Marketplace, a private health insurance market. Individuals whose household income is below 400% of the year are eligible for subsidies in the form of Premium Tax Credits. The amount of this subsidy will be determined jointly by insurance premium and their household income. Generally, the higher the income is, the lower amount of tax credit they will receive. Also, if individuals purchase plans with a standard lower than a silver plan, the more they pay in premiums, the more subsidies they will receive.

[3] The amount of subsidy is determined by one's household income relative to FPL and the price of health care plan. Higher income will lead to a lower amount of credit. Details can be found at: https://www.irs.gov/pub/irs-pdf/i8962.pdf

As a complement to the private insurance market, the Affordable Care Act also expanded the scope of public health insurance. Starting in 2014, the upper income threshold for enrolling in Medicaid has risen from 100% of FPL to 138% of FPL. 100% of Federal Poverty Level becomes another important threshold which distinguishes the population who are newly eligible for Medicaid under the new policy. The change of criteria expanded the base of poor population and so a larger poor population is able to enroll in government-run health care plan to cover their basic medical needs and no longer have to purchase private health care plans.

Meanwhile, a mandate is also proposed along with the prior two policies. To reach the goal of universal coverage, all individuals are required to have Minimum Health Care Coverage the entire year, although there are some exceptions such as the case when the costs of premium is higher than certain percentage of the household income and lack of coverage for fewer than three months. Violators without an exemption will be required to pay a fine through their tax return. The amount of fine increased from $95 in 2004 to $695 in 2016. Therefore, it becomes a strong incentive for individuals with low income to obtain health care coverage to avoid a fine.

The Affordable Care Act is a major change of how medical services are delivered and how insurance industry performs. Moreover, it is impacting individuals' decisions on medical and insurance premium expenditure. While the expenses on medical service has skyrocketed, the health care coverage rate remained stable in U.S. for long term and leaving a portion of poor population our of the medical system. Therefore, I am interested in studying how effective the reform is on benefiting the US low-income population and how the ACA change individuals decisions on their lives. My study focus on two goals of the ACA; one of its goal is to expand the participation in health care plan, and another one is to reduce health related expenditure. Since healthcare coverage and medical costs are essential indicators of health care system performs in a country, by studying the change in these to indicators, I can have some insights into how effective the reform is.

It is reasonable to assume that the general coverage rate will increase after the implementation of ACA. A mandate which applies to nearly all population is a drive. One reasonable speculation based on the policy change is that the general coverage rate should increase. By far, few researchers have investigated and quantify the increase in health care coverage rate due to ACA at a national level. While many researchers are interested in general variation of coverage, it is also interesting to focus on coverage rate change at a smaller scope. The new policy introduced two important thresholds. With a clear cutoff on income relative to the Federal Poverty Level, individuals with similar ratio can be impacted differently. One who has a relative ratio right below the cutoff can receive subsidies on health care coverage, while one who has income to FPL ratio slightly above threshold won't be able to receive benefit, even though the difference of two ratios is very small. By focusing on the threshold, we can measure the impact of subsidy with minimum effect from income variable. The result of comparing coverage rate of groups whose income to FPL ratio below and above the cutoffs can reveal the impact of eligibility on people's choices of whether to have health care coverage.

Among all age groups, teenagers might have a higher increase in healthcare coverage rate compared to other age group. New policy allows children and young adults to participate in patents' plan. This policy is similar to a former study conducted by Kolstad and Kowalski (2012) about Massachusetts health care, which shows that teenage and young adults have significant increase on their coverage rate. Other policies in the ACA, such as the mandate that allows children and young adults to participate in patents' health care plan, originates from the Massachusetts health care reform. Due to a lower risk of health concern of children and young adults, their parents and themselves might not realize the need of purchasing a health insurance plan. If young adults can participate in their parents' plan, lower premium cost might attract more enrollment from younger population.

2. Literature

Since the ACA is relatively new, it takes time for research result to be generated. However, Massachusetts' 2006 health care reform, which has similar policies compared to the Affordable Care Act, has drawn attention for being able to potentially predict the results of the implementation of the Affordable Care Act at a national level (Kolstad & Kowalski, 2012). The Massachusetts reform has been considered a regional experiment of the ACA. Massachusetts health care reform is similar to the ACA in many ways. They both subsidized low and moderate income families for health insurance and expand Medicaid in order to reach universal health care coverage. A mandate for health care was valid later. Children under 26 are allowed to be covered under parents' insurance. Pre-existing medical condition can no longer stop children from getting health care. Employers exceeded certain size are required to cover health care for their full-time employees who work over 30 hours per week.[4] In many perspectives, the Massachusetts health care reform corresponds to the ACA. Some results from the study of Massachusetts might give inspirations on finding impacts of the Affordable Care Act.

Kolstad and Kowalski (2010) examined the impact of 2006 reform from various aspects, such as health care coverage percentage, on difference population demographics. Compared to other states in U.S. who did not implement a health care coverage mandate and corresponding policies, Massachusetts experienced an increase in healthcare coverage rate among different

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[4] Companies with over 50 employees are required to sponsor insurance. A penalty up to$3240 will be imposed if the employer fails to cover 95% of the full-time employees.

population groups after the reform. Private insurance coverage offered by employers contribute the largest growth to increase in health care coverage rate. Moreover, the increase is mainly from non-elderly population below 75% income percentile, especially those whose income is in the second quantile. Looking at the admission to hospital, their data also indicates that the admission to emergency room and length of stay in hospital both declined, implying people's awareness on physical health and sickness prevention is improved. In other words, their health status therefore is enhanced as the health reform is enforced.

Long, Stockley, and Nordahl's study (2012) confirmed the increase on health care coverage of adults. They also found that the health care spending has a less proportion of family income after the reform. Less individuals reported to have problem paying medical bills. These findings indirectly confirm my speculation that the ACA will decrease the individual spending in health care and medical bills. Their study found that improvement of access to insurance is most observable on children and young adults, although a general increase on coverage rate and access to medical services.

Other reform on health care also shows similar increase on coverage rate. Johnston discussed the effectiveness of a mandate of Medicaid enacted in 1991. The rate of coverage on poor population, especially women and children, had significantly increased(Johnston, 1997). Four to five million more poor children and women received Medicaid. Moreover, over four million elderlies newly admitted to the program, which expanded the effect of Medicaid mandate even further. As the third largest source of health care insurance in the U.S., this increase expanded the health care coverage especially on the population on a poor spectrum. The result of this study can support the assumption that a mandate on health care coverage will have positive effect on coverage rate for poor families and individuals.

After the application of Massachusetts, we have better anticipation on the impact of policies in the act. Nonetheless, although Massachusetts performed a similar health care reform, this state level health reform will not capture the complexity of health reform in a national level with variation across states (Kolstad & Kowalski, 2012). Thus, the topic I am studying is a meaningful step to not only confirm the estimation of health care reform impact based on Massachusetts result, but also an exploration on impacts that are not obvious at state level. A nationwide study with a large range of demographic features helps the study to be more general model rather than limited model to explain variations in subgroups. Furthermore, unlike most studies mentioned above that used difference-in-difference model to estimate the impact of health care reform globally within the sample, I decide to focus on a local impact caused by the policy change. Since several policies in the ACA propose thresholds for various benefits, it would be helpful to focus at the threshold to identify any abrupt change within the sample and evaluate the treatment effect b. In this way, my study would not only be able to study the impact of the act, but also separate the effect of various policies and evaluate them individually by focusing similar groups at around the threshold. Economists would also be interested in this question as it involves the effectiveness of this policy. They can also gain empirical evidence on how subsidies and mandate change people's choice on health care and even general consumption. Policy makers can utilize the research results to evaluate the impact of the health care reform and improve the health care policy in the future to achieve their goal.

3. Data Description

To conduct analysis, I mainly utilized the dataset from American Community Survey(ACS), a nationwide self-reported survey that conducted every year to collect different perspectives of an individual' status such as education, health care and employment information.

Households and individuals are randomly selected regardless of their races household income, ages, etc. With responses from over 300,000 individuals each year, the data set has a large size and is reliable.

There are many variables available for researcher to use, including individuals' household income level, number of family members, age, gender, work status, race, marital status, and health care coverage status, etc. Dummy variables are crucial to examine one's benefit reception status. Therefore, it is necessary to include dummies that identify whether one's income is below threshold, whether someone has health care coverage, and whether the year is after the implementation of the ACA.

I choose this dataset over Current Population Survey (CPS) on analyzing health care coverage due to its clear source of health insurance. It contains variables identifying whether an individual obtains coverage through public healthcare or private health and the exact plan one participates in. Moreover, with a variable specifying birth quarter of each individual, I have more flexibility on grouping using age as the standard. A large sample size of ACS stabilizes regression models and minimizes variance the impact of each observation has on the model.

On the other hand, to study the expenditure of medical services and health insurance premium, I selected data from Current Population Survey (CPS) as it has more detailed information of individuals' health care sources and expenses. CPS is another nationwide survey to collect self-reported household and individual information. Although CPS is smaller in sample size, it is more feasible for CPS to collect more parameters that cover wider aspects of one's life, which gives researchers freedom to focus on their interested variables.

In my study, I mainly focus at non-elderly adults ages from 18 to 65 to study their coverage status. They are adult that represent the majority in the society. The timeframe of data is from 2010 to 2015. Based on their household income relative to Federal Poverty Level, individuals are separated in to several groups to examine their coverage rate. About 1.4 million observations in total are available for analysis after applying restrictions age, time and relative household income. When I use dataset from CPS, I followed similar selection rules and obtained 85448 observations in my dataset.

4. Methodology

4.1 Regression Discontinuity Design

To discuss the effect of different policies in the Affordable Care Act, I chose to use regression discontinuity design (RDD) as the main tool to investigate any local effect imposed on certain populations. Regression discontinuity design has become popular in recent decades to estimate treatment effect in a non-experimental setting. Imbens and Leieux (2007) discuss how to use RDD to identify the effect of a binary intervention and therefore recognize the variation in an interested variable due to the intervention. Samples would be separated into two groups based on the numeric value of a certain variable compared to a fixed cut-off criterion. The relative location of the value solely determines whether a unit in the study receives treatment. Instead of the entire sample, only the observations whose covariate value is close enough to the pre-determined threshold will be studied. Generally, the selected observations will demonstrate similar traits on other aspects except that those on one side of the cut-off will receive treatment and those on the other side will not.

One of the benefits of regression discontinuity design is that its outcome can be easily observed through plots. A discontinuity, the treatment effect researchers try to identify, can usually be spotted at a figure with a clear gap through visualization. **Figure 4.1.1** demonstrates a visualization of a discontinuity regression design. Without noticing the treatment effect, the interested covariate would display a smooth function through the interval we are studying. However, if the treatment effect exists, a discontinuity of function of two sides of the cutoff would appear, and the magnitude of the gap would be the treatment effect we are interested in. Lee and Lemieux (2010) summarized that RDD only requires fewer assumptions to be fulfilled. In a non-experimental setting, the model is useful as a continuity assumption on other variables would be enough to support the validity of the model. Nonetheless, this assumption is difficult to rigorously verified.

Since in the Affordable Care Act, the thresholds of eligibility to receive health care benefit are clearly defined, it is practical to apply RDD in this situation. Whether an individual receives benefits from the act solely depends one aspect of his or her status, such as age, household income and employment status, etc. In this way, regression discontinuity design is capable of capturing the treatment effect imposed to target population by comparing them with a similar group whose criterion variable has the value right of the other side of the pre-determined threshold. These two groups are similar in most ways except that one receives the treatment and the other does not. Regression discontinuity is applicable in this situation to identify the magnitude of treatment effect from the policies by comparing an interested value from one group to the other.

4.2 Assumptions

To have a valid model of regression discontinuity design, one underlying assumption of RDD is that individuals did not voluntarily choose to the position relative to the cutoff, which means observations are distributed smoothly across the interval of the interested covariate. It ensures that no significant distribution difference exists to weaken the explanatory power of the potential treatment effect we find in the design. Otherwise, the treatment effect will be biased and invalid due to the failure of local randomization (Lee & Lemieux, 2010).

Moreover, to eliminate the impact from other variables, we need to check if the same discontinuity appears in other variables. Failure to fulfil this assumption would undermine the credibility of treatment effect in the case that instead of the imposed intervention, the discontinuity in other covariates could potentially explain the origin of treatment effect.

4.3 Regression

The following regression model is used to systematically measure the effect of the ACA:

$$
\begin{aligned}
Y_{it} = \beta_1 * Controls_{it} + \beta_2 * \ (Distance\ from\ Threshold)_{it} + \ \beta_3 \\
* \ (Distance\ from\ Threshold)_{it}^2 + \ \beta_3 * (Treatmeat)_{it} + \beta_4 * After\ 2014_{it} \\
+ \ \beta_5 * (Treatmeat)_{it} * After\ 2014_{it}
\end{aligned}
$$

In this regression, Y_{it} represents the interested outcome variable for individual *i* in year *t* (eg. Health care coverage rate, out-of-pocket expenses); *Controls* specifies any variables that are potentially predictive to the outcome variable;[5] the linear and quadratic terms of the distance of an from policy threshold (eg. 400% of FPL) helps center the data and eliminate biased impact from the distance. *Treatment* is a dummy variable and *After 2014* is a dummy variable to simply

[5] A few variables that I include in model when discussing policy effect are education (receive college education or not), age, employment status, race (white or non-white), marital status and numbers of children. They are mostly dummy variables except for age and numbers of children, which are multi-level categorical data.

mark the time of the observation; the interaction of *Treatment* and *After 2014* represents the treatment effect of policies that I am interested in.

5. Empirical Specifications and Results

5.1 Inspecting the impact of subsidies on privately-purchased insurance

I am interested in how the health care reform affects families and individuals whose household income is around the 400% Federal Poverty Level to conclude a causation relationship between variation of health care coverage and the policy of subsidies on privately insured individuals. By focusing on the observations around the cutoff line, I can identify impacts that happen locally.

To investigate the effect, I focus on the population whose household income is between 350% to 450% OF FPL. Based on their household income relative to FPL, I divided the sample into 50 groups with a band width of 2% of FPL to calculate their average health care coverage rate. In this way, each side of the 400% of FPL threshold has 25 groups of observations. **Figure 5.1.1** demonstrates the distribution of individuals in group. The number of individuals in each group does not have a significantly large difference. In particular, several groups that are close to the threshold have similar amount of observations, suggesting that individuals do not have an incentive or capability to manipulate their income relative to the threshold, which confirms the validity of regression discontinuity design. Thus, it indicates that the treatment group and controlled group are equivalent to being randomized, which means individuals in both groups start from similar baseline. This perception gives explanatory power of regression discontinuity design in studying the treatment effect of subsidy that has a sharp cutoff at 400% of FPL.

In **Figure 5.1.2**, a smooth continuous regression of coverage rate before 2014 versus household income relative to FPL is desirable since neither group faced subsidy benefit nor fine penalty without a health care plan. We can estimate how health care subsidy impacts the coverage rate of health care by looking at the gap of change in coverage rate before and after the ACA implementation.

After I checked that the assumption of local randomization holds, I applied the regression discontinuity design to investigate the problem. To better demonstrate the result of regression discontinuity, **Figure 5.1.3** is generated to display the increase in coverage rate across different groups. By plotting the average health care coverage rate within each group and comparing the result before and after the ACA implementation, I can fit regression lines of relative income versus change in average coverage rate on both sides of the threshold. Fractional polynomial regression fits scatter points the best, and other two regressions act as a robustness check for the result. I noticed that the scatter points generally locate above the 0% line, indicating that the coverage rate is higher after the policy implementation generally. Two policies are jointly affecting the change of coverage rate. An individual health insurance mandate is imposed on all individuals, which leads to an approximately 2.8% increase in general coverage rate on the groups that have household income above 400% of FPL. As they are not eligible for subsidies on private health, this increase would most likely be due to the mandate. On the other hand, the groups whose household income is below 400% of FPL are eligible for subsidies, and they seem to have roughly the same magnitude of increase in general coverage rate. A discontinuity at threshold is not found in the plot, indicating that the subsidies itself does not give people strong an incentive to obtain health insurance. Three types of regression fit all converge and support the finding that there is no significant discontinuity happened at threshold due to the subsidies on privately-purchased health insurance. In other words, the subsidies on privately-purchased insurance does not seem to be effective on encouraging eligible population to obtain health care coverage.

To quantify the model, I fitted the data into an empirical specification as followed:

$$Coverage_{it} = \beta_1 * Controls_{it} + \beta_2 * (Relative\ Household\ Income - 400\%)_{it} + \beta_3 * (Relative\ Household\ Income)_{it}^2 + \beta_3 * (income < 400\%\ of\ FPL)_{it} + \beta_4 * After\ 2014_{it} + \beta_5 * (income < 400\%\ of\ FPL)_{it} * After\ 2014_{it}$$

Coverage is a dummy variable (coverage = 1 means if an individual has minimum health care coverage) presents the coverage rate that I am interested in, and it is the outcome variable in the empirical specification. I have introduced control variables including a dummy variable on gender, race (white or non-white), employment status, marital status. Linear and quadratic terms of difference between relative income and 400% of FPL help identify the effect of income difference in this specification. *After 2014* is a time dummy variable to represent whether the observation is after the enforcement of mandate 2014. *Income<400%* is also dummy variable to classify an observation in terms of household income relative to Federal Poverty Level. β_4 is the coefficient that I am most interested in as it is the coefficient of the interaction term. If this coefficient is statistically different between low income families after the reform enacted, it demonstrates that the health reform policy has a causal impact on the interested outcome variable.

By fitting the empirical specification mentioned before, **Table 5.1.1** is generated. The variable post shows positive significance, illustrating that after the mandate the overall coverage rate is increased by 0.7% in all observations. Whether an individual's household income is below the 400% of FPL does not make a difference on their decisions on getting health care coverage. The interaction term, which is crucial in RDD, has a positive significant coefficient. Yet, the coefficient is only 0.59%, which is so minor that we are unable to notice at figure 5.1.3. Meanwhile, I also use public insurance coverage rate and private insurance coverage rate as outcome variables to run the same specification. The results returned present similar information. The significant positive coefficient of the model indicates that the coverage rate of both types of insurance increase at about 1%. Yet, increase in coverage rate due to subsidies, which is reflected as the coefficient of interaction term is small for public insurance coverage and insignificant for private insurance. Overall, the results in empirical specification confirm my finding in the visualization plot that the subsidies on privately-purchased health insurance did not improve people's willingness to obtain health care coverage.

To eliminate the possibility that the data on farther ends of FPL intervals strongly affect the result of empirical specification, I did a robustness check by trimming the 1%, 5% and 10% tails on two end of interval. I utilize the same specification mention above but modify the sample that I used in each check. The results are shown in **Table 5.1.2**. The coefficients of interaction term in all models maintain at around 0.5% with over 95% confidence. Meanwhile, the coefficient of time variable is stable at about 2.8% among the four models, demonstrating that the individual mandate has caused a 2.8% increase on coverage rate, and the effect of subsidies is robust but minor.

5.2 Inspecting the effect of Medicaid expansion on population at 100% of FPL

Next, I investigate the impact of Medicaid expansion by focusing at 100% of FPL as the benefit threshold. After ACA expands the scope of Medicaid, now individuals whose household income is between 100% and 138% of FPL are newly eligible for Medicaid, while individuals whose relative income is below 100% of FPL are not affected by the expansion of Medicaid since they are already qualified using the former criterion. The only change that this population receives is the individual health care mandate that requires them to obtain minimum coverage. Studying non-elderly adults aged from 18 to 65 whose family income is between 62%-138% of FPL will be meaningful to investigate the expansion of Medicare program and its effect. I divided the sample into 38 groups with 2% of FPL bandwidth.

The continuous assumption can be confirmed by the relatively even distribution of observations based on their relative household income in **Figure 5.2.1**. This figure shows the distribution of individuals at around 100% Federal Poverty Level, the cutoff of scope of Medicaid after the ACA expansion of public health care. It confirms that individuals did not precisely control their income to FPL ratio at around 100% since there is no obvious trend of leaning toward either side. It is reasonable to confirm this necessary assumption and build foundation on the validity of regression discontinuity design. In other words, a regression discontinuity is supported in this study with current sample by verifying that local maximization at around 100% cut-off exists.

Although we would expect some treatment effect on the observations that are newly eligible for the program, it is surprising to find no significant discontinuity in **Figure 5.2.2**. visualization of the observations grouped by their relative household income to FPL, and it graphically confirms the finding in model result.

For each group, the health care coverage rate after and before ACA implementation are calculated and compared. A discontinuity is not obvious in this plot, which confirmed an insignificant interaction term in the result. Both regression lines shown in the figure are close to horizontal, showing that income to FPL ratio does not have an impact on coverage rate change.

The expansion of Medicaid also does not have significant effect on increasing health care coverage rate of population with low income. Yet, an interesting finding is that all the difference between coverage rate after and before mandate are positive. They mostly range from 0.05 and 0.20, and both regression lines have intercept at approximately 0.12-0.13. The large positive differences corresponded to the coefficient of the post variable and further assured the result in regression model that overall coverage rate increased due to the implementation of fine. It demonstrated an overall increase in coverage rate after the ACA implementation, and indicated that to lower-income families, a fine is stronger drive to encourage them to obtain health care. When I look into the change of mean coverage rate of different groups after the policy is imposed, Figure 5.2.2 demonstrates. The result is approximately 11-12% increase on both side.

After fulfilling the pre-assuming condition, local randomization, by fitting the data into a similar model we have previously, a new empirical specification is obtained:

$$\begin{aligned} Coverage_{it} = \beta_1 * Controls_{it} + \beta_2 * \ (Relative\ Household\ Income - 100\%)_{it} + \ \beta_3 \\ * \ (Relative\ Household\ Income - 100)_{it}^2 + \ \beta_3 \\ * (income < 100\%\ of\ FPL)_{it} + \beta_4 * After\ 2014_{it} + \ \beta_5 \\ * (income < 100\%\ of FPL)_{it} * After\ 2014_{it} \end{aligned}$$

This specification controls same variables in section 5.1. Instead of using 400% of FPL, I substitute it with 100% of FPL as cutoff. **Table 5.2.1** is regression result of the model. Although the coefficient of the interaction term in this model is positive and significant across three types of coverage rate, the value of coefficient is less than 1%, indicating a minor effect of the expansion.

The expansion of Medicaid does not have a strong causal increasing impact on the population with household income slightly above 100% of FPL based on this result. While we can conclude that whether an individual's household income is below 100% does not affect its possibility of getting health insurance, it is interesting to see that the increase after implementation of the ACA post variable shows significance with a coefficient equals to 11.23% with 95% confidence, indicating a strong confirmation that the variable is indeed crucial in this model. This result is intuitive, as after the mandate of health insurance, individuals who are not covered will face a fine up to $695. This is a large financial burden to low income population, in particular for families whose income is close to the Federal Poverty Level. Therefore, since the coverage rate of health care rises across the entire interval that we studies, and the individual health care mandate is applicable to all individuals, it is reasonable to state that the consequence of paying a fine could be the main drive that population at around 100% of FPL obtained health insurance after the mandate is imposed.

I am also interested in studying young adults who are between age 19-26 as the y only have a 70% of health care coverage rate. The interaction term of this model studying general coverage rate of young adults shows significance and has a value of 1.76%. It indicates that the expansion of Medicaid contributes to a 1.76% of increase in coverage rate. However, its effect is still not as dominating as the individual health care mandate. After 2014, the coverage rate on both groups around age 26 has a 12.92% increase based on the model results. It seems that the expansion of Medicaid is effective on improve health care participation, but the individual mandate plays a primary role on raising coverage rate of the young adults.

As a last step to confirm the validity of the model, I ran the empirical specification with data whose tails are trimmed to avoid bias from extreme values at the tails of sample distribution based on income relative to FPL. Results in **Table 5.2.2** confirms that the tails are not influential in this model as the interaction coefficient are approximately same as the full model without trimming the tails.

5.3 Inspecting the effect of mandate on employers to cover dependents under age 26

Besides benefits provided by the government to encourage the general public to obtain health care, the act also imposes mandate on employers to protect the benefits of employees and their families. One of the mandates that required employers to contribute to the employees' dependent's health care coverage draws my interest as young adults are generally considered the group with lower coverage rate. This policy would help employees' dependents to stay in their parents' employer-sponsored health care plan up to age 26. Therefore, it is meaningful to study the coverage rate on employer-sponsored health care on dependents under 26. I choose to focus on the age interval of 22-29 as young adults in this age range share many common traits. I further select individuals who are unemployed with personal annual income below $54000. This group of population is unable to receive health care benefits from their own employers due to their employment status. They also have low income and are likely to receive support from their parents, indicating that they are the targeted individuals in this policy.

I naturally decide to use age 26 as a fixed cutoff to study how coverage rate changes for young adults. ACS data has specified the birth quarter of each observation, which helps me separate observations aged from 22-29 into 32 groups, each of which are one of the combinations of ages (8 groups) and quarters (4 in a year). Distribution of individuals is smooth using the combination of age and birth quarter as grouping criterion. By looking at **Figure 5.3.1**, the change of frequency in different age group is smooth, and there is no abrupt change at threshold age 26. Meanwhile, age is one of a few factors that cannot be voluntarily changed. Therefore, the assumption of local randomization is valid.

The young adults above age 26 face the individual mandate after the practice of ACA, yet they are no longer eligible for health care covered by their parents' employer. Meanwhile, although the younger adults are required to have health care coverage as well, they are able to fulfill that requirement through their parents' plan. To observe the change of coverage due to this policy difference in age 26, the most direct method is to observe whether there is the discontinuity of coverage rate change at 26 years old cutoff. In **Figure 5.3.2**, I plot out the increase in coverage rate of each group in the selected sample after the implementation of ACA in 2014. Interestingly, the discontinuity is considerably large at the threshold age 26. Generally, the young adults have a higher health coverage rate after 2014, as we notice that nearly all scatter points locate above 0%, indicating a general expansion of employer-sponsored plan coverage. Moreover, the groups whose age is below 26 have approximately 6% increase on coverage rate, while the older group on average has less than 2% of increase in in employer-sponsored plan coverage rate. Taking the difference of these two increases, it leads to the magnitude of the gap occurring at age 26. This discontinuity implies that the mandate imposed on employers is effective on increasing the employer-sponsored coverage rate by roughly 4%.

To study the treatment effect quantitatively, I ran the model in the following form of empirical specification:

$$Coverage_{it} = \beta_1 * Controls_{it} + \beta_2 * \ (Age - 26)_{it} + \ \beta_3 * \ (Age - 26)_{it}^2 + \ \beta_3 * (Age < 26)_{it} + \beta_4 * After\ 2014_{it} + \ \beta_5 * (Age < 26)_{it} * After\ 2014_{it}$$

The empirical specification of this model is similar to the prior models, except that I fit general coverage, public health care coverage, private health care coverage and employer-sponsored coverage separately as outcome variables to estimate the impact of this requirement imposed by ACA. Furthermore, since I limit the sample to be unemployed and low-income, I decide to drop employment status from control variables and includes the linear and quadratic terms of one's personal annual income. The results are shown in **Table 5.3.1**. The coefficient of the interaction term in the specification studying employer-sponsored coverage rate is statistically significant and has a value of 4.37%, which corresponds to the gap we noticed at threshold in figure 5.3.2. The coefficient of variable specifying year after 2014 is also significant and matches the magnitude displayed in regression discontinuity figure. They jointly demonstrate that the mandate is implemented successfully to improve the employer-sponsored coverage rate of young adults under 26.

By comparing the coefficients of the interaction terms in models that use public health care coverage and private health care coverage as outcome variable, I noticed that the new policy not only have an impact on employer-sponsored coverage rate, but also affect people's choice of obtaining public health care. It is reasonable that the interaction term in private health care model has a significant coefficient with value of 3.99% since employer-provided plan for dependents is one subcategory of private health care. The policy of enforcing coverage on dependents under 26 effectively raises the coverage rate of private health care. However, looking at the coverage of public health care among young adults, it is interesting to identify a negative coefficient for interaction term in the model studying public health care coverage. Its coefficient is significant with a value of -2.98%, implying that while the policy leads to an increase coverage in private health care, the coverage rate in public health care declines. and we cannot rule out the possibility that young adults leave their public health care plan and switch to a private health care under their parents' employer-provided insurance. Overall. The comparison between public and private insurance coverage of young adults suggests that private insurance is more preferable for young adults after the ACA implementation, which are likely to either provide better medical coverage or at a lower cost.

I have fitted fractional polynomial, linear and quadratic regression forms on age versus coverage rate on figure 5.3.2, and they all share similar trend and location, indicating the robustness of the increase, which is in form of a discontinuity occurring at threshold age 26, of employer-sponsored health care coverage rate for eligible population due to the mandate on employers. To test robustness of the model quantitatively, I also run models using the original sample but trim tails on both sides of the age interval that I am interested in. By eliminating 5% and 10% of the data on both tails of age, the coefficients of model results do not show significant variation. All model results in **Table 5.3.2** seem to remain stable and confirm the validity of the conclusion that employer-sponsored insurance for dependents under 26 has a larger participation rate due to ACA mandate on employer.

Furthermore, to fulfill the continuity assumption of RDD and to eliminate the potential bias from discontinuity in other covariates, I identify that income and education status might be two factors that need to be observed. By separately plotting them against age, no significant discontinuity is found no two plots (**Figure 5.3.3** and **Figure 5.3.4**). Therefore, the validity of the model is confirmed by robustness check.

5.4 Inspecting the change of medical costs at 400% of FPL

Besides improving the participation in health care, another goal of the Affordable Care Act is to lower the financial burden on medical fields. Studying the variation of out-of-pocket expenses and health care premium would be essential to get insights of the impact of the ACA. In this section, I use Current Population Survey data obtained from IPUMS as it has health care expenses information available from 2010 to 2015, yet the sample size is much smaller than CPS, which has about 85000 observations. I am interested in identifying the change of expenses in medical expenses and health care premium at 400% to evaluate the effectiveness of the Affordable Care Act. It would be helpful to study if the subsidies on privately-purchased health care have any impact on financial aspect. In this case, I decide to study the first person of households whose income is between 300%-500% of FPL. 100 groups of household with 2% of FPL will be generated to further study the mean change of households as a collection.

Since I have verified the local randomization of sample population at around 400% in prior models, I assume the validity of regression discontinuity design in this situation. Focusing on each family's 1st recorded person, I calculate the out-of-pocket medical expenses per person, and premium costs per person based on family status, as well as total cost per person, which is the sum of out-of-pocket medical expenses and premium costs in per person term. After conducting analysis on total costs, the results are displayed in **Figure 5.4.1**. This figure illustrates the relationship between income relative to Federal Poverty Level and increase in total medical cost after the ACA practice. Even though the subsidies program is supposed to alleviate the financial burden on low-income families, it does not show any significant difference on variation of total medical costs after 2014 compared to those families who are not eligible for subsidies, which is demonstrated by the continuous scatter strip across the 400% of FPL threshold. No obvious gap occurs at the 400% of FPL cut-off, implying that the treatment effect of subsidies on privately-purchases healthcare offered to low-income families is neglectable. Although the effect of treatment is insignificant, it seems that after 2014 the total costs general rises. It is unexpected that data points mostly located above the \$0 baseline. It shows that on average the total costs per person that go to health-related services is about \$400 higher than before 2014, which contradicts to the goal of the ACA

I run the following empirical specification to verify the finding from discontinuity plot:

$$Expenses_{it} = \beta_1 * Controls_{it} + \beta_2 * \ (Relative\ Household\ Income - 400\%)_{it} + \ \beta_3 * \ (Relative\ Household\ Income)_{it}^2 + \ \beta_3 * (income < 400\%FPL)_{it} + \beta_4 * After\ 2014_{it} + \ \beta_5 * (income < 400\%FPL)_{it} * After\ 2014_{it}$$

The specification analyzes total costs, out-of-pocket expenses and premium costs per person as outcome variables and includes other control covariates[6], and the change on costs are presented quantitatively in **Table 5.4.1**. The interaction term of total costs model is insignificant, which confirms the finding in figure 5.4.1. General increase in total costs on both sides of the threshold is about \$351.56, which is close to the magnitude shown in the figure. Moreover, by comparing the coefficients form models of out-of-pocket expenses and premium costs, I notice that both models show general higher costs after 2014 regardless of the eligibility to receive subsidy. Out-of-pocket expenses on average rises \$179.37, and premium costs increase by about \$172.20. two coefficients add up to approximately the value of total costs increase. Therefore, it is likely that out-of-pocket and premium costs simultaneously rise regardless of the health care coverage status. The coefficient of the interaction term in the model studying medical premium is a negative term, indicating a potential decrease of premium costs due to the subsidies on

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[6] Control covariates include the first person's college education status, age, linear and quadratic terms of difference between relevant percentage of FPL and 400%, marital status and numbers of child.

privately-purchased insurance. Although it is a reasonable statement since the subsidies directly lower the premium cost for eligible individuals, there is not enough significant statistical proof supports the impact on subsidies in practice. One possible explanation for the increase of total cost could be the intervention of government activities. The new policy in the ACA imposes mandates on buyers and more restrictions on the seller side, which could limit the free market and cause lower efficiency.

Lastly, a tail trimming robustness test also confirms the credibility of conclusions drawn from the discontinuity figure and specification results. **Table 5.4.2** reflects that after trimming the tails of 300%-500% of Federal Poverty Level, the main coefficients vary little from the model with full data. Moreover, the significance level of parameters does not change as I remove observations far from the threshold. The result confirms that observations at farther ends of the FPL interval have little impact of the coefficients. Therefore, I confirm the validity of specification results.

6. Discussion

By running several regression models based on different policy criteria in the ACA, I come up with some findings regarding the effectiveness of the ACA. Although I have run robustness check on all models to confirm the validity of model results, some factors in my study are restraining the explanatory power of my models.

The data that I choose to use is in national level as I am estimating a program that runs nationwide. Nonetheless, with such a large geographical scale, I failed to collect variables to represent the variation among states. In the data set that I obtained from ACS, the geographical variables for at individual level are unavailable. Thus, I was unable to introduce geographical difference in my models when estimating treatment effect. Although the ACA is at the federal level, each state still has freedom on its implementation, leading to distinction among states.

Furthermore, the difference also exists at the individual level. Although I have captured many factors that potentially have predictive power on outcome variable, some expected factors are either hard to collect or difficult to standardize and quantify. The Affordable Care Act is a complex health care reform that involves a considerable number of guidelines. I conducted my analysis based on the general guideline, yet it might not be applicable to some individuals. For instance, the mandate would have no impact on someone if he or she is qualified for an exemption from penalty. In this case, the policy is no longer affecting one's decision making. However, by analyzing the data obtained from ACS will produce have no insight in this portion of the population. More importantly, if individuals who are not affected are falsely placed in the treatment group, their presence can reduce any possible treatment effect that we try to identify in the model.

Since the Affordable Care Act has just passed in recent years, and many policies have been implemented in 2014, I was only able to obtain two years of data after the practice of the ACA. The time frame that I concentrate on is between 2010 and 2015, which is relatively short when evaluating the effectiveness of policy, it might be vulnerable if more data are available to use for research. This might lead to an unstable model and as we collect more data in the future, the current model might not still be valid and useful. Therefore, future research might want to continue to obtain data and try to minimize the distinction between different states and individuals to produce a more stable model with convincing explanatory power.

7. Conclusion

Overall, some impacts of the ACA are confirmed through several models that I studied. ACA is assured to cause a higher health care coverage rate generally across all subgroups that I studied. The main driver is likely to be the individual health mandate that applies to the entire population. Another mandate that requires employers to cover dependents of their employees up to the age of 26 is enforced. This policy effectively covers more young adults with employer-sponsored health insurance plan. Meanwhile, a dip in public health care coverage is found simultaneous, suggesting that young adults choose to participate private insurance plan over public health care.

There is two program that allows low-income families to obtain minimum health coverage with less financial burden. The subsidies on privately-purchased health care does not contribute to an increase of coverage rate of its targeted individuals. although the general coverage rate of low-income families increases after the Medicaid expansion, Medicaid did not lead to an improvement of coverage rate of the newly eligible population relative to the control group. Although the ACA's original goal is to reduce costs and alleviate financial difficulties on paying for health care and medical services, the model result shows an increasing trend of costs, which contradicts to policymakers' intention.

Based on model results, mandates that imposed a fine are showing a stronger impact on improving health care participation. Both Medicaid and subsidies are expected to be an incentive for people to get health care at a lower cost, yet the analysis in this study does not confirm the effectiveness of financial encouragement. In the future, any policymaker who plans to draft a health care plan should take it into consideration utilize an appropriate method to receive goals of expanding coverage and lowering costs.

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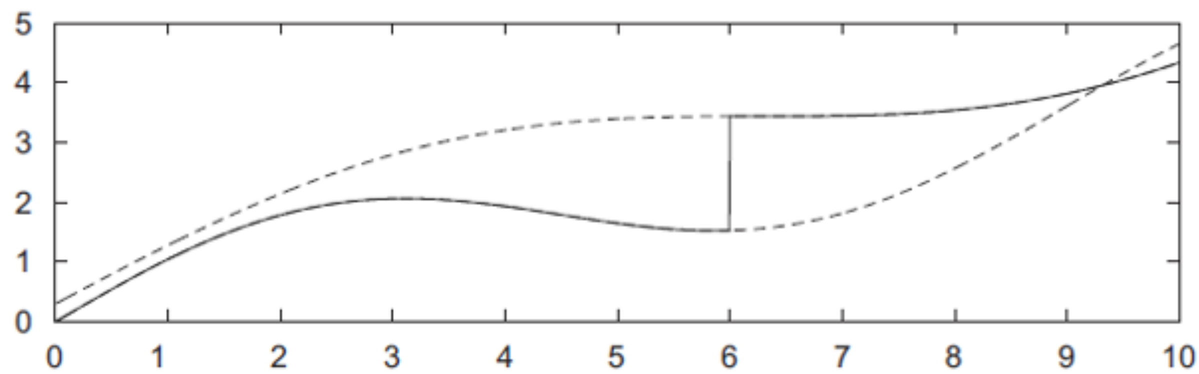
Appendix

Figure 4.1.1 Regression Discontinuity Visualization



Source: The plot is obtained from "Regression Discontinuity Designs: A Guide to Practice". *Journal of Econometrics* written by Imbens, G., & Lemieux, T. (2007).

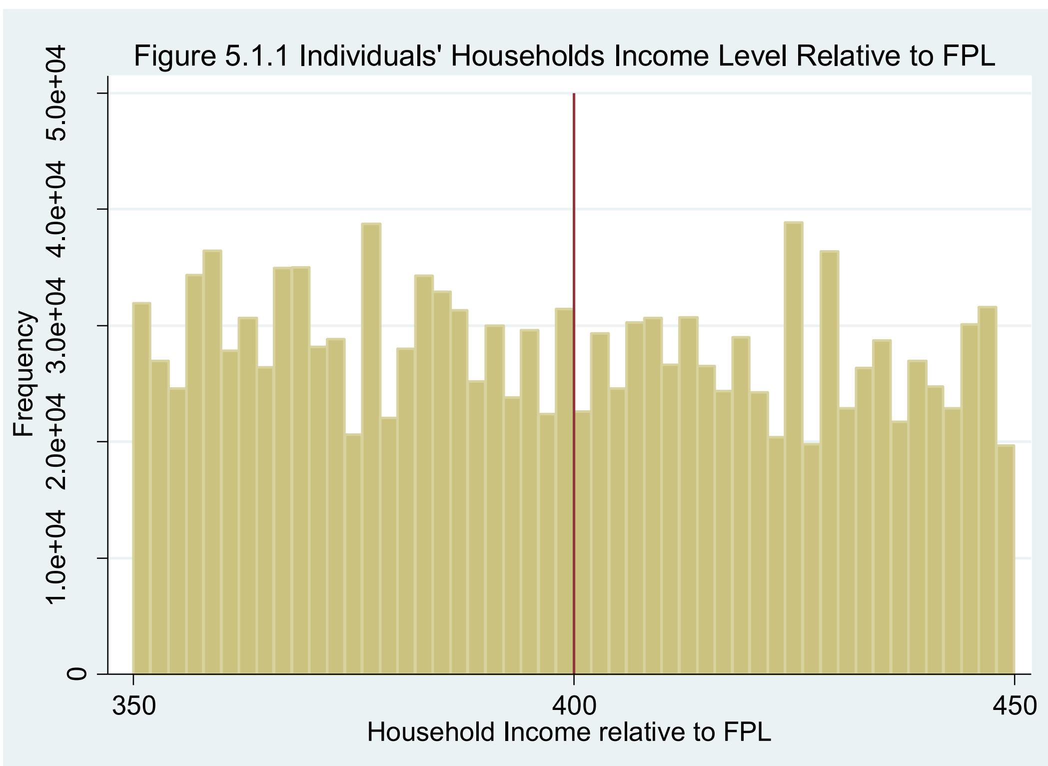


Figure 5.1.1 Individuals' Households Income Level Relative to FPL

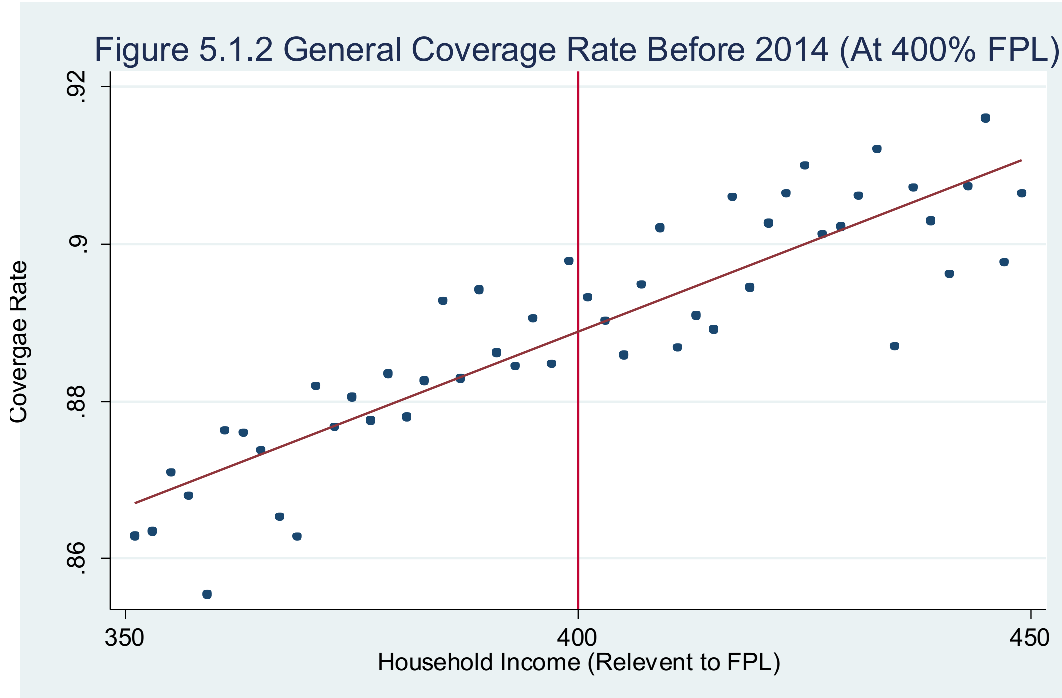


Figure 5.1.2 General Coverage Rate Before 2014 (At 400% FPL)
Covergae Rate
.86
.88
.9
.92
350
400
450
Household Income (Relevent to FPL)

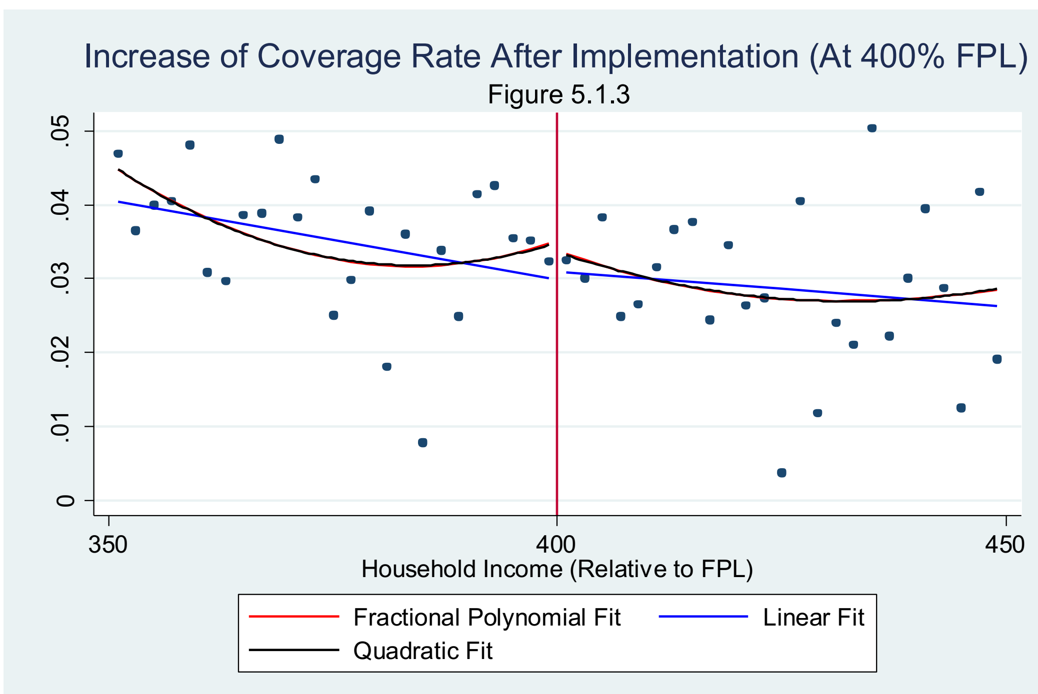

Increase of Coverage Rate After Implementation (At 400% FPL)
Figure 5.1.3
0
.01
.02
.03
.04
.05
350
400
450
Household Income (Relative to FPL)
Fractional Polynomial Fit
Linear Fit
Quadratic Fit

Table 5.1.1 Specification Result at 400% FPL

	(1) General Coverage Rate	(2) Public Health Care Coverage	(3) Private Health Care Coverage
After 2014	0.0279**	0.0109**	0.0167**
	(0.0007)	(0.0007)	(0.0009)
Below 400% FPL	-0.0010	-0.0023*	0.0006
	(0.0010)	(0.0010)	(0.0012)
Interaction	0.0059**	0.0078**	0.0017
	(0.0010)	(0.0010)	(0.0012)
N	1405992	1405992	1405992
R^2	0.0428	0.0451	0.0558
adj. R^2	0.0428	0.0451	0.0558

Standard errors in parentheses
Note: Control variables includes education, race, age, gender, employment status, linear and quadratic terms of difference between relevant percentage of FPL and 400% FPL, marital status and numbers of child.
+ $p<.10$, * $p<.05$, ** $p<.01$

Table 5.1.2 Robustness check: Trimming tails

	(1) General Coverage Rate	(2) Trimming 1% Tails	(3) Trimming 5% Tails	(4) Trimming 10% Tails
After 2014	0.0279**	0.0280**	0.0283**	0.0287**
	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Below 400% FPL	-0.0010	-0.0009	-0.0013	-0.0005
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
Interaction	0.0059**	0.0055**	0.0051**	0.0043**
	(0.0010)	(0.0010)	(0.0011)	(0.0011)
N	1405992	1379451	1269296	1125528
R^2	0.0428	0.0427	0.0423	0.0423
adj. R^2	0.0428	0.0427	0.0423	0.0423

Standard errors in parentheses
Note: Control variables includes education, race, age, employment status, gender, linear and quadratic terms of difference between relevant percentage of FPL and 400% FPL, marital status and numbers of child.
+ $p<.10$, * $p<.05$, ** $p<.01$

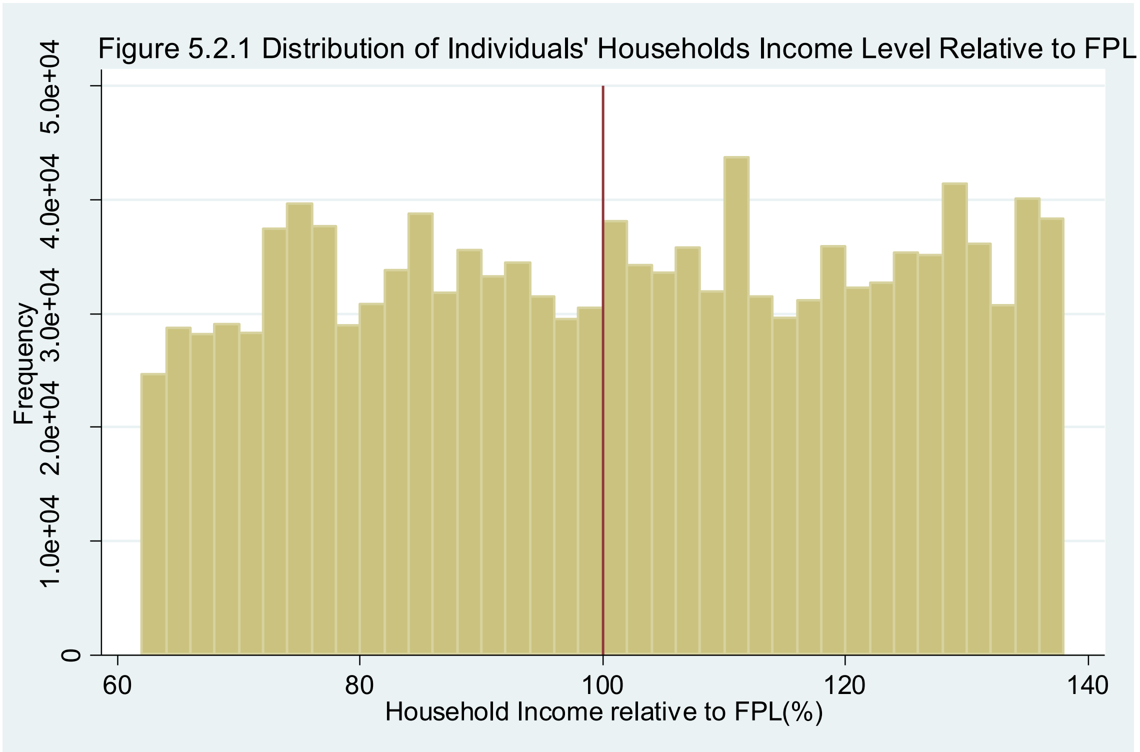


Figure 5.2.1 Distribution of Individuals' Households Income Level Relative to FPL
Frequency
0
1.0e+04
2.0e+04
3.0e+04
4.0e+04
5.0e+04
60
80
100
120
140
Household Income relative to FPL(%)

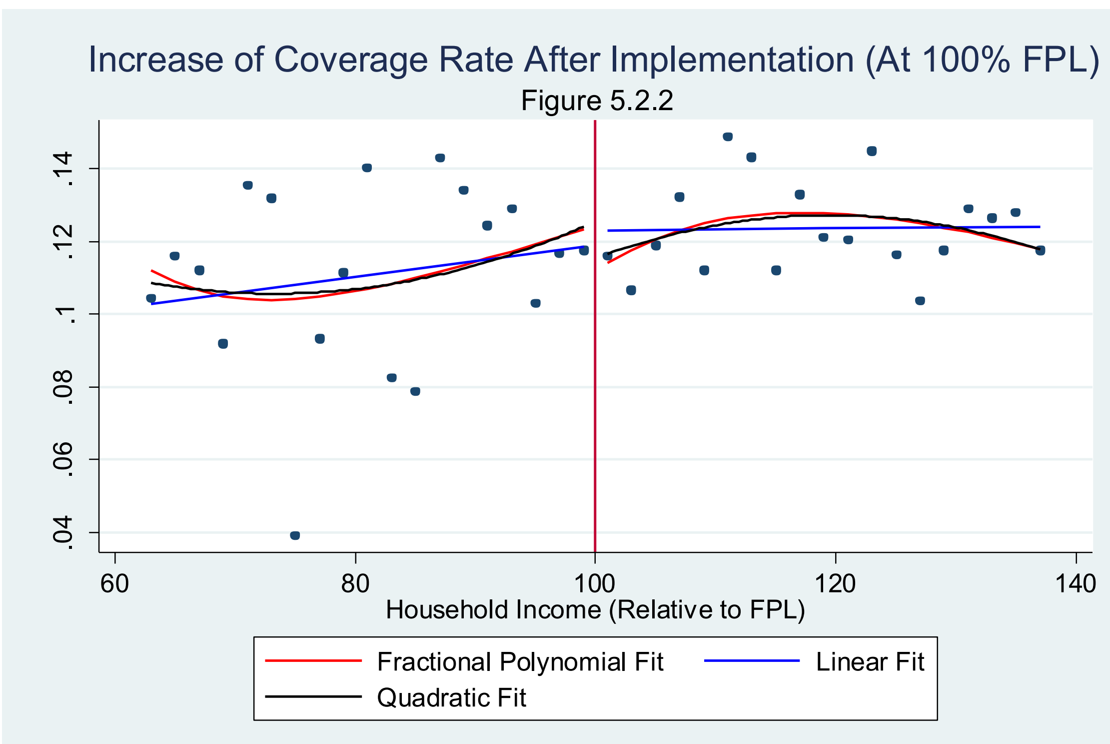

Increase of Coverage Rate After Implementation (At 100% FPL)
Figure 5.2.2
.04
.06
.08
.1
.12
.14
60
80
100
120
140
Household Income (Relative to FPL)
Fractional Polynomial Fit
Linear Fit
Quadratic Fit

Table 5.2.1 Specification Results at 100% FPL

	(1) General Coverage Rate	(2) Public Health Care Coverage	(3) Private Health Care Coverage	(4) General Coverage Rate (Age 18-26)
After 2014	0.1123**	0.0860**	0.0335**	0.1292**
	(0.0012)	(0.0012)	(0.0012)	(0.0026)
Above 100% FPL	-0.0086**	-0.0125**	0.0046**	-0.0083*
	(0.0016)	(0.0016)	(0.0015)	(0.0034)
Interaction	0.0105**	0.0041*	0.0083**	0.0176**
	(0.0017)	(0.0017)	(0.0016)	(0.0036)
N	1472794	1472794	1472794	330650
R^2	0.0476	0.1545	0.0945	0.0569
adj. R^2	0.0476	0.1545	0.0945	0.0569

Standard errors in parentheses
Note: Control variables includes education, race, age, employment status, gender, linear and quadratic terms of difference between relevant percentage of FPL and 100% FPL, marital status and numbers of child.
+ $p<.10$, * $p<.05$, ** $p<.01$

Table 5.2.2 Robustness Check at 100% FPL

	(1) General Coverage Rate	(2) Trimming 1% Tails	(3) Trimming 5% Tails	(4) Trimming 10% Tails
After 2014	0.1080**	0.1075**	0.1066**	0.1073**
	(0.0013)	(0.0013)	(0.0013)	(0.0014)
Above 100% FPL	-0.0098**	-0.0092**	-0.0020	0.0115**
	(0.0017)	(0.0017)	(0.0018)	(0.0019)
Interaction	0.0111**	0.0105**	0.0133**	0.0117**
	(0.0017)	(0.0018)	(0.0018)	(0.0019)
N	1280914	1255880	1153041	1024946
R^2	0.0393	0.0392	0.0401	0.0415
adj. R^2	0.0393	0.0392	0.0401	0.0415

Standard errors in parentheses
Note: Control variables includes education, race, age, employment status, gender, linear and quadratic terms of difference between relevant percentage of FPL and 100% FPL, marital status and numbers of child.
+ $p<.10$, * $p<.05$, ** $p<.01$

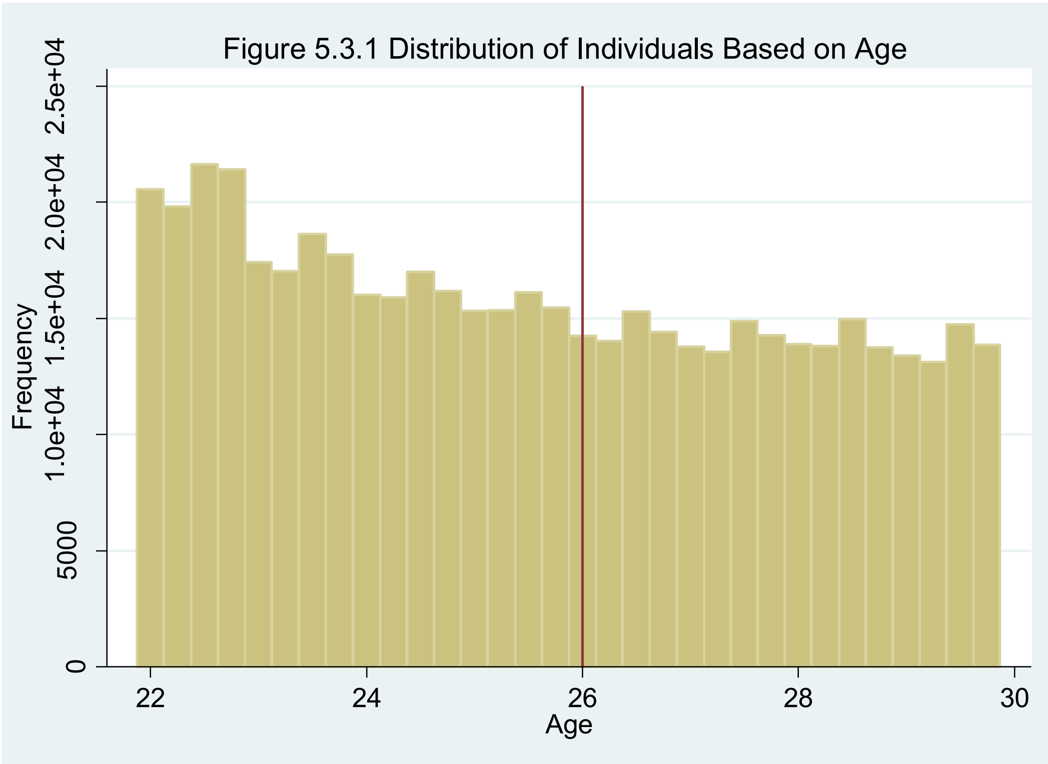


Figure 5.3.1 Distribution of Individuals Based on Age
Frequency
0
5000
1.0e+04
1.5e+04
2.0e+04
2.5e+04
22
24
26
28
30
Age

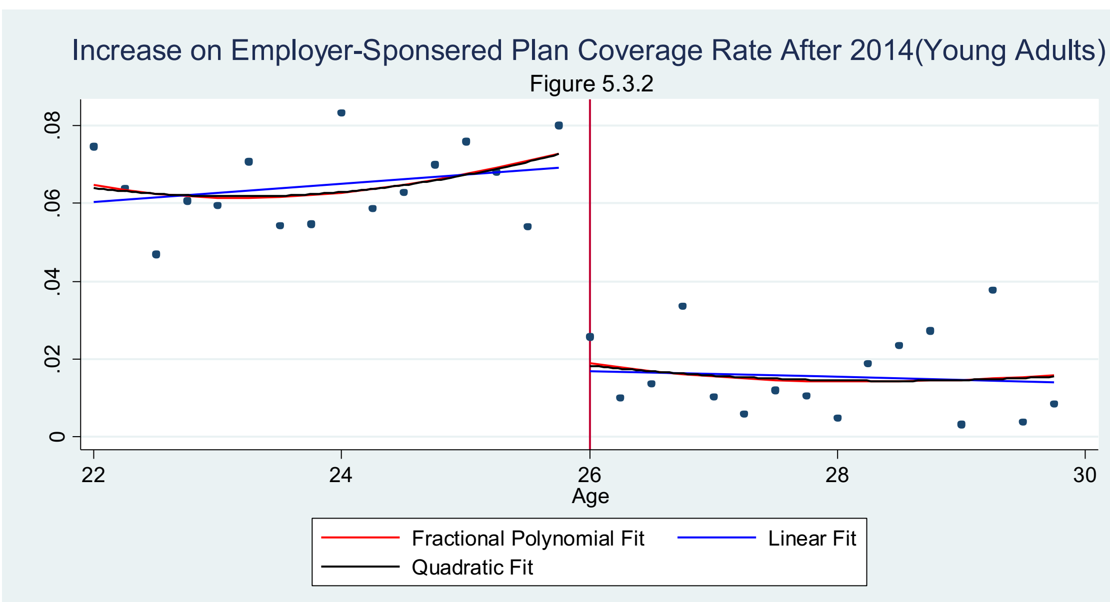

Increase on Employer-Sponsered Plan Coverage Rate After 2014(Young Adults)
Figure 5.3.2
0
.02
.04
.06
.08
22
24
26
28
30
Age
Fractional Polynomial Fit
Linear Fit
Quadratic Fit

Table 5.3.1 Empirical Specification Result: Comparing Coverage Rates of Young Adults

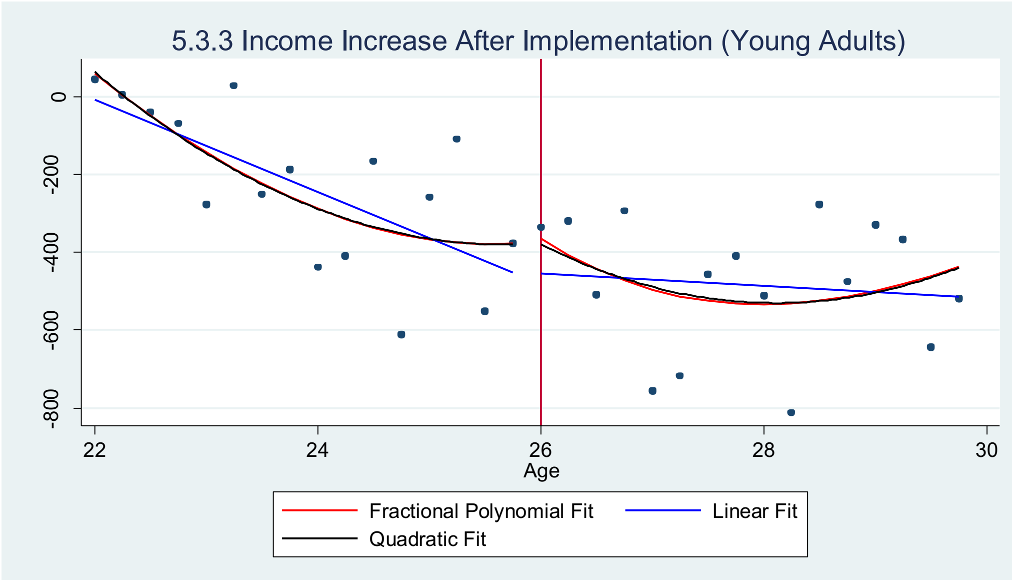
	(1) General Coverage Rate	(2) Public Health Care Coverage	(3) Private Health Care Coverage	(4) Employer-sponsored Coverage
After 2014	0.1052**	0.0808**	0.0354**	0.0129**
	(0.0021)	(0.0019)	(0.0019)	(0.0018)
Below age 26	0.0279**	0.0020	0.0298**	0.0424**
	(0.0028)	(0.0026)	(0.0027)	(0.0025)
Interaction	0.0098**	-0.0298**	0.0399**	0.0437**
	(0.0028)	(0.0026)	(0.0026)	(0.0025)
N	507502	507502	507502	507502
R^2	0.0973	0.1210	0.2181	0.1371
adj. R^2	0.0972	0.1210	0.2180	0.1371

Standard errors in parentheses
Note: Control variables includes education, race, gender, linear and quadratic terms of difference between age and 26 years old, linear and quadratic terms of personal income, marital status and numbers of child.
+ p<.10, * p<.05, ** p<.01

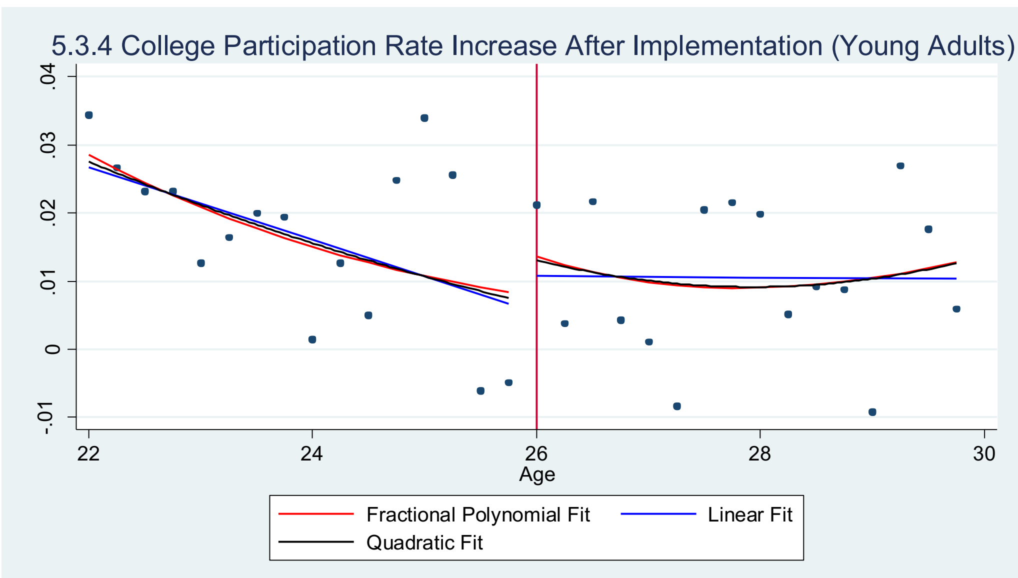
Table 5.3.2 Robustness Check of Empirical Specification Results (Young Adults)

	(1) Employer-sponsored Coverage	(2) Trimming 5% Tails	(3) Trimming 10% Tails
After 2014	0.0131**	0.0135**	0.0146**
	(0.0018)	(0.0019)	(0.0020)
Below age 26	0.0425**	0.0432**	0.0449**
	(0.0025)	(0.0026)	(0.0027)
Interaction	0.0436**	0.0433**	0.0435**
	(0.0025)	(0.0026)	(0.0027)
N	507502	473098	425449
R^2	0.1368	0.1343	0.1303
adj. R^2	0.1367	0.1343	0.1302

Standard errors in parentheses
Note: Control variables includes education, race, gender, linear and quadratic terms of difference between age and 26 years old, linear and quadratic terms of personal income, marital status and numbers of child.
+ p<.10, * p<.05, ** p<.01



5.3.3 Income Increase After Implementation (Young Adults)
0
-200
-400
-600
-800
22
24
26
28
30
Age
Fractional Polynomial Fit
Linear Fit
Quadratic Fit



5.3.4 College Participation Rate Increase After Implementation (Young Adults)
.04
.03
.02
.01
0
-.01
22
24
26
28
30
Age
Fractional Polynomial Fit
Linear Fit
Quadratic Fit

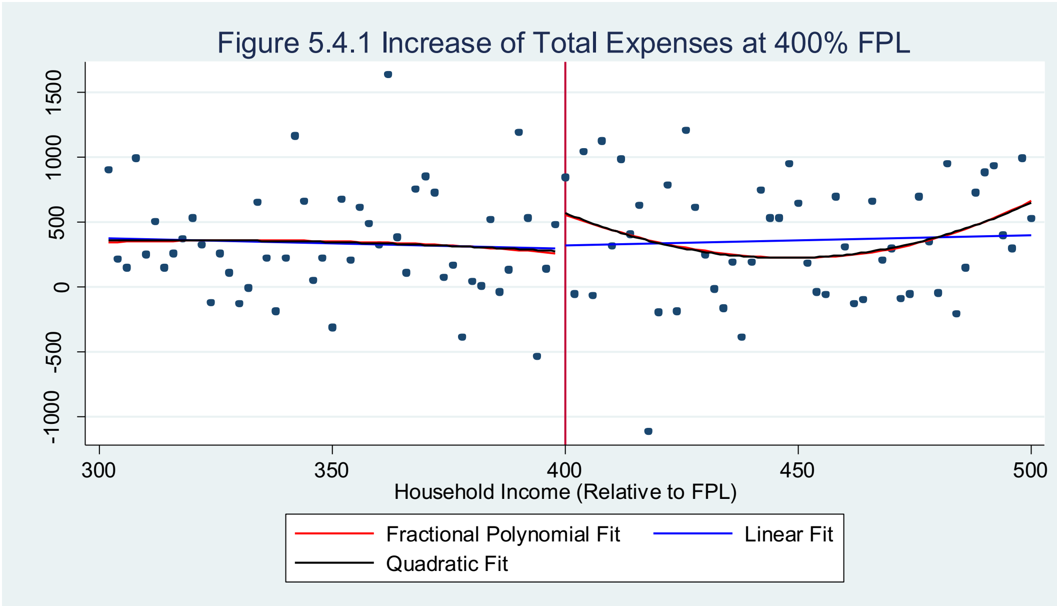


Table 5.4.1 Empirical Specification Results

	(1) Out-of-Pocket Costs	(2) Premium Cost	(3) Total Costs
After 2014	179.3561**	172.2024**	351.5585**
	(36.1502)	(15.4923)	(46.2168)
Below 400% FPL	3.3713	-15.4721	-12.1008
	(47.2997)	(20.2705)	(60.4711)
Interaction	-16.9277	-38.7053+	-55.6330
	(48.3352)	(20.7142)	(61.7949)
N	85448	85448	85448
R^2	0.0317	0.0593	0.0477
adj. R^2	0.0316	0.0592	0.0476

Standard errors in parentheses

Note: Control variables includes whether received college education, age, family coverage, linear and quadratic terms of difference between relevant percentage of FPL and 400%, marital status and numbers of child.

+ p<.10, * p<.05, ** p<.01

Table 5.4.2 Robustness Check Results

	(1) Total Costs	(2) Trimming 1% Tails	(3) Trimming 5% Tails	(4) Trimming 10% Tails
After 2014	351.5585**	346.5680**	317.9370**	347.5315**
	(46.2168)	(46.5118)	(49.3558)	(52.7747)
Below 400% FPL	-12.1008	1.5494	3.5426	14.1885
	(60.4711)	(60.8522)	(64.5147)	(68.8633)
Interaction	-55.6330	-56.8875	-23.5930	-54.6898
	(61.7949)	(62.1433)	(65.6296)	(69.7474)
N	85448	83740	76917	68369
R^2	0.0477	0.0479	0.0467	0.0470
adj. R^2	0.0476	0.0478	0.0466	0.0468

Standard errors in parentheses

Note: Control variables includes whether received college education, age, linear and quadratic terms of difference between relevant percentage of FPL and 400%, marital status and numbers of child.

+ p<.10, * p<.05, ** p<.01