**Diagnosis Unclear? – The ACA, Medicaid, and Labor Supply Revisited**

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**University of Colorado Denver**

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1. **Introduction**

The Patient Protection and Affordable Care Act, also known as the Affordable Care Act (ACA) for short, and colloquially called “Obamacare,” has been controversial since it was proposed in 2009 and subsequently passed and signed into law in 2010. It seems that one of the primary reasons for the controversial nature of this law is how it fits into the long running policy debate in the U.S. about whether public assistance programs reduce labor supply due to reduced work incentives. Indeed, the CBO estimated in 2014 that the ACA would reduce labor supply due to provisions like private health insurance subsidies and the Medicaid expansion (Harris & Mok, 2015).

A few papers have attempted to empirically study the effects of the Medicaid expansion, finding more or less null results, Gooptu et al. (2016), Leung & Mas (2016), Kaestner et al. (2017), Peng et al. (2018).All but one of these studies used a difference-in-difference research design with an indicator for Medicaid expansion in 2014 as the independent variable of interest and state & year fixed effects. It is plausible, even likely that the repeated null results of the standard DiD studies are a result of a lack of statistical power rather than a true zero. Under the DiD research design using state-level identifying variation (indicator variable for Medicaid expansion in 2014), there is little variation with which to estimate this effect: there are only 50 observations (states), the “treatment” variable is binary, and most studies drop early and/or late expanding states, reducing the sample size for the independent variable as low as 36.

In addition, these DiD studies rely on a relatively implausible identifying assumption: that Medicaid expanding states and non-expanding states would be on the same trends in labor market outcomes over time, absent the ACA. This amounts to assuming that there are no factors differentially affecting outcomes of expansion and non-expansion states over time, which could reasonably be violated by such confounders as state level economic conditions or population growth. As Courtemanche et al. (2017) note, this seems a particularly strong assumption “given the political nature of the Medicaid expansion decision and the possibility that unobserved determinants of 2014 coverage changes could be correlated with a state’s political climate.” Indeed, Courtemanche and coauthors go on to cite Sobel (2014), which provides evidence that republican state leadership was highly predictive of not expanding Medicaid.

Furthermore, only one study has attempted to examine the effect of the broader ACA in addition to the Medicaid effect on labor supply, Duggan et al. (2017). This study also attempts to improve upon the little identifying variation of the DiD Medicaid studies by utilizing a research design similar to the triple difference/dose response model of Courtemanche et al. (2017). Unfortunately, the specifics of the research design used seem overcomplicated, and make the estimated effects difficult to interpret. In any case, Duggan and coauthors find mostly null results, with the key exception being an association between the non-Medicaid ACA provisions rolled out in 2014 (notably the private insurance exchanges) and a modest decrease in labor force participation.

This paper contributes to the existing literature on the ACA and labor supply by examining the effects of both the Medicaid expansion and the broader ACA, using more data (through 2016, 2015 was the latest year used in aforementioned studies), and making use of a research design with more identifying variation/statistical power and a weaker identifying assumption than the DiD Medicaid studies.

I accomplish this by employing the triple difference/dose response (DiDiD) methodology of Courtemanche et al (2017). The additional statistical power over the DiD Medicaid studies is a result of the addition of pre-expansion uninsured rates in local areas as a dose/treatment intensity variable. In other works, areas which had more uninsured individuals can expect to get a higher “dose” of the Medicaid expansion than areas with less uninsured individuals. This increases the sample size and identifying variation with which effects on labor supply can be estimated. This research design, importantly, allows me to separately estimate the effects of the 2014 ACA “non-Medicaid” provisions on labor supply. It is important to note that local area uninsured rates (the dose variable) must be measured prior to the ACA rollout/Medicaid expansion in 2014 because these uninsured rates subsequently declined as a result of the policy, which was a major goal of the ACA. In contrast to the DiD Medicaid specifications, the DiDiD model does not rely on the identifying assumption that there are no factors differentially affecting outcomes of expansion and non-expansion states over time, but rather, that any such factors are not correlated with pre-reform uninsured rates. I estimate this model using ACS Data (2011-2016), and data on state Medicaid expansions from the Kaiser Family Foundation. My outcome variables are log wages, labor force participation, employment and hours worked.

Results of my study indicate that the ACA Medicaid expansion was not significantly associated with labor supply, possibly with the exception of labor supply for females, although these estimates were not statistically significant. The non-Medicaid ACA provisions, however, seem to be associated with a substantial and statistically significant increase in employment. This estimated effect ranges from an increase in employment of 0.2 percentage points for the minimum uninsured PUMA to an increase in employment of 2.6 percentage points for the maximum uninsured PUMA, or an increase of 1.1 percentage points for the average PUMA.

The rest of this paper is laid out as follows. Section II provides useful background information on the ACA, Medicaid, and labor supply. Section III examines previous literature relevant to this study. Section IV describes the data sources used in my analysis. Section V outlines my empirical methodology. Section VI reports results of my analysis. Section VII presents robustness checks, and section VIII concludes.

1. **Background**

The Affordable Care Act was a sweeping reform that signifies the largest change to the U.S. healthcare system in generations. While the law was passed in 2010, many of the key provisions did not take effect until 2014. Among these aspects activating in 2014 were the Individual Mandate, the insurance exchanges (and subsidies), the Medicaid expansion, and many insurance regulations, such as the pre-existing conditions protection (Advisory Board, 2013). While the employer mandate was originally scheduled to take effect in 2014 as well, this provision was delayed until 2015.

The Medicaid expansion endeavored to extend Medicaid eligibility to all adults below 138% of the Federal Poverty Line (FPL). While the Medicaid expansion was originally intended to apply to all states, the Supreme Court ruled in *National Federation of Independent Business v. Sebelius (2012)* that states could not be compelled to expand Medicaid against their wishes. As a result of this decision, many states elected to not expand their Medicaid programs, creating useful variation for those wishing to study the effects of the Medicaid expansion.

Prior to the passage of the ACA, not all low-income adults were required to be covered by Medicaid: “The federal government only required that states provide Medicaid to children, pregnant women, parents of dependent children, individuals with disabilities, and qualifying people over age 65. States were not required to cover childless, low-income, non-disabled adults” (Health Reform Tracker, 2017). While these were just the minimum requirements, and some states had more generous eligibility rules, many did not. Moreover, states were only required to cover only the poorest among us: “In 2013, before the ACA Medicaid expansion took effect, the median state Medicaid income eligibility cut-off for working parents was 61% FPL and, in most states, non-elderly adults without dependent children (“childless adults”) were categorically ineligible for Medicaid” (Paradise, 2016). Given these facts, we would not expect the Medicaid expansion to increase health coverage uniformly across demographic groups.

Indeed, studies have documented that the ACA, and specifically, the Medicaid expansion, increased health coverage, especially for a few subgroups. For instance, Courtemanche et al. (2017) find that, on average, “the full ACA increased the proportion of residents with insurance by 5.9 percentage points compared to 2.8 percentage points in states that did not expand Medicaid,” and that the coverage gains were concentrated in individuals “without a college degree, non‐whites, young adults, unmarried individuals, and those without children in the home.”

Some who are critical of the ACA (and other public assistance programs) have argued that the Medicaid expansion, would create more government dependency by reducing work incentives and therefore work effort (labor supply). This leads to the question “Why might Medicaid affect work?”

Simple microeconomic theory suggests that the Medicaid expansion may affect work effort in a few different ways. Health insurance is quite expensive, and government provided health insurance is therefore worth a lot of money, especially given that Medicaid coverage eliminates most out-of-pocket costs in addition to premiums. Therefore, there is a significant income effect of receiving Medicaid coverage, ie. one can work less and consume the same amount as before. This income effect alone may be enough to induce some individuals to decrease work effort, and there may be additional distortionary effects for individuals who are near the new or old eligibility income thresholds. Individuals just above the new eligibility threshold may reduce work effort to obtain Medicaid if their lost income is less than the income effect of Medicaid. Finally, individuals who were reducing work effort to obtain Medicaid coverage under the old eligibility thresholds may increase work effort now that this can be done without losing Medicaid coverage. The predicted overall effect of the Medicaid expansion on work effort is therefore ambiguous and must be studied empirically.

The mechanisms by which the non-Medicaid ACA provisions could affect labor supply are less obvious. In chapter 50 of *The Handbook of Labor Economics*, “Health, health insurance and the labor market,” the authors Currie & Madrian outline two primary mechanisms by which employer provided private health insurance could affect labor supply (p. 3376). First, there is a direct tradeoff between wages and fringe benefits for firms. This means that increasing the value of benefits provided to employees such as health insurance should lead to decreased wages through cost shifting. Second, the costs of losing health insurance upon changing jobs could lead some to stay in at their current job even when better alternatives are available. This concept is referred to as “job lock,” and has received a good deal of attention in the conversation around health insurance in the United States.

Note that these outlined mechanisms are for employer provided private health insurance, not individually purchased private health insurance. Currie & Madrian do note, however, that health insurance of any kind could have a direct positive effect on labor supply if it increases health, although empirical literature on this is sparse, due to identification issues. However, the authors also explain that health insurance could have an indirect effect on labor supply if increased health changes the tradeoff between leisure and work. This hypothesized effect could go in either direction depending on an individuals’ preferences.

1. **Literature Review**

There is a relatively robust empirical research literature on the effects of public health insurance and labor supply in the US. A few studies are worth noting. Baicker et al. (2013) examine the Oregon health insurance experiment, in which people were randomly assigned to receive Medicaid, and find a small decrease in employment and earnings. While this estimate is not statistically significant, the experimental nature of the context studied gives me increased confidence in the estimated effect. Garthwaite et al. (2014) study the 2005 TennCare disenrollment, in which about 170,000 people suddenly lost Medicaid coverage, and find a statistically significant increase in employment. Note that this result suggests that the presence of Medicaid coverage was *reducing* employment. Finally, Dague et al. study the 2009 extension of Medicaid to childless adults in Wisconsin, and find a statistically significant decrease in employment.

A few papers have looked specifically at the effect of the ACA Medicaid expansion on labor market outcomes using DiD research designs. These papers use an indicator variable for the Medicaid expansion decision in 2014 as identifying variation and include state & year fixed effects. Gooptu et al. (2016) examine transitions from employed to unemployed, transitions from full-time to part time employment, and job switches using data from the monthly CPS (through 2015), and find no significant effects. Leung & Mas (2016) study employment, hours worked, and wages using ACS data through 2014, and find no significant effects. Kaestner et al. (2017) analyze whether an individual is employed at time of interview, usual number of hours worked per week, whether an individual works more than 30 hours per week (full-time) using data from the ACS through 2014, monthly CPS through 2015, and the March CPS through 2016, and find no significant results. Most estimates were positive, note the authors.

Additionally, two recent papers have studied the Medicaid expansion and labor supply with different research designs. Peng et al. (2018) examine employment and wages using a unique research design with data from the Quarterly Census of employment and wages. Peng and coauthors compare bordering county-pairs from expansion and non-expansion states, make heavy use of fixed effects (county, year, county-pair, county-pair-by-year) and find “a small but statistically significant decrease in employment of 1.3 percent one year after the Medicaid expansion.” The authors note that this effect dissipates within two years, and they do not find any significant effects on wages, “at any point.” Duggan et al. (2017) examine the ACA and labor supply using a methodology similar to the triple-difference/dose response specification of Courtemanche et al. (2017). However, rather than utilizing pre-reform uninsured rates as the dose response variable, as in Courtemanche et al. (2017) and other ACA literature, Duggan and coauthors define their own dose response variables (two) based on pre-reform uninsured rates of particular income groups. They then estimate two specifications similar to DiD/dose response and DiDiD/dose response, but utilizing both dose response variables in the same equation. The authors find a modest decrease in labor force participation, although the magnitude seems difficult to interpret given their specification.

1. **Data**

This paper makes use of two data sources: the American Community Survey or ACS (2011-2016), and the Kaiser Family Foundation. The ACS is a large-sample (~3.5 million) household survey which is conducted throughout the year and released annually by the U.S. Census Bureau. The Kaiser Family Foundation is an American non-profit organization focused on healthcare, and more specifically, providing policy analysis, research, news and information related to healthcare.

I utilize the ACS for labor market outcomes (my dependent variables), demographic controls, and pre-expansion uninsured rates (the treatment dose/intensity variable for the DiDiD model). Data on whether a state expanded Medicaid in 2014 comes from the Kaiser Family Foundation. For my primary analysis, I have limited my sample to adults aged 25-55 (prime working ages), in order to limit adult students and early retirees in the sample. Notably, my primary sample is not selected based on characteristics like income or education, as is common in the literature, although I do estimate heterogeneous effects by education.

The Kaiser Family Foundation, on their website, identify several states which expanded their Medicaid programs after January, 2014: Michigan, New Hampshire, Pennsylvania, Indiana, Alaska, Montana, Louisiana, Maine, and Virginia (Kaiser Family Foundation, 2018). Additionally, Kaestner et al. (2017) identify four states (and Washington, D.C.) as having comprehensive Medicaid expansions prior to 2014: Delaware, Massachusetts, New York, and Vermont. These “late expanding” and “early expanding” states (including DC) are dropped from the sample for my main analysis.

As mentioned, I utilize sub-state geographic variation in pre-reform (2013) uninsured rates to provide additional statistical power over the standard Medicaid DiD specifications. Unfortunately, the ACS does not contain data from all counties, only large ones, so county level uninsured rates are not feasible to use. The next smallest geographical unit present in the ACS is the Public Use Microdata Area or PUMA, a sub-state geographic unit used by the U.S. Census Bureau for providing demographic/statistical information. Fortunately, there is a complete set of PUMAs present in the ACS.

However, the definitions of PUMAs change every ten years after the Census. In order to facilitate intertemporal analysis, the ACS also provides a “2000/2010 constant PUMA” variable which combines 2000 Census PUMAs and 2010 Census PUMAs into one normalized variable. Due to the fact that the 2010 Census PUMAs were not adopted until 2012, and that I add 2009 & 2010 ACS data for a robustness check, I make use of the constant PUMA variable for my analysis. I therefore use pre-expansion uninsured rates by constant PUMA as my dose response variable. These rates were created using the indicator variable for any health coverage in the 2013 ACS data. Note that henceforth I will refer to constant PUMAs, simply as PUMAs.

Summary statistics of the variables used in the analysis are presented in Table 1. While Employed, Labor Force Participation, and Employed were native in the ACS, Hourly Wage had to be created by dividing Wage Income by Usual Hours Worked times 52 weeks per year. Additionally, outliers in wage have been dropped (wage < $1 or wage > $1000). It is important to note that I use the natural log of hourly wage in my analysis as levels are difficult to interpret.

Note that the sample size on Employed, Usual Hours Worked, and Wages are lower than the overall sample size of 5,597,891 due to the fact that some people are not in the labor force or are unemployed, and therefore have missing values for some or all three of these variables. Additionally, coding individuals who are unemployed or not in the labor force as missing for wages allows me to examine log wages without dropping anyone from my sample. Note that both employment and labor force participation are very high in my sample due to the fact that the sample has been limited to the primary working age population, individuals aged 25-55. Furthermore, I created age dummy variables, ages 25-35, ages 35-45, and ages 45-55 for use as controls and for heterogeneous effects. For ease of computation, I use aggregate data in this analysis. Sample sizes are a bit all over the place due to the fact that my heterogeneity and robustness analysis required that the dataset be collapsed by some of the demographic controls as well as by PUMA, state, and year.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 1: Individual Level Summary Statistics** | | | | |
|  | Mean | Min | Max | N |
| **Outcomes** |  |  |  |  |
| Employed | 0.935 | 0 | 1 | 4469191 |
| In Labor Force | 0.798 | 0 | 1 | 5597891 |
| Hourly wage | 23.13 | 1 | 1000 | 4187685 |
| Usual Hours Worked Per Week | 40.438 | 1 | 99 | 4511167 |
|  |  |  |  |  |
| **Independent Variables** |  |  |  |  |
| PUMA Uninsured Rate, 2013 | 0.210 | 0.040 | 0.518 | 5597891 |
| Medicaid Expansion in 2014 | 0.547 | 0 | 1 | 5597891 |
|  |  |  |  |  |
| **Controls** |  |  |  |  |
| Female | 0.506 | 0 | 1 | 5597891 |
| Age | 40.768 | 25 | 55 | 5597891 |
| College (Some College +) | 0.565 | 0 | 1 | 5597891 |
| Hispanic | 0.172 | 0 | 1 | 5597891 |
| Black | 0.105 | 0 | 1 | 5597891 |
| Asian | 0.061 | 0 | 1 | 5597891 |
| White | 0.632 | 0 | 1 | 5597891 |
| Other Race | 0.030 | 0 | 1 | 5597891 |

1. **Methodology/Empirical Strategy**

In order to investigate the effect of the Medicaid expansion on labor supply, I start by estimating the standard difference-in-differences model from the literature, to establish a baseline which I will compare to findings from previous literature:

where is average wage income, usual hours worked per week, labor force participation, or employment for PUMA *a* in state *s* in year *t*, is an indicator equal to 1 if state *s* expanded Medicaid during the 2014 expansion, is an indicator equal to 1 for the post-expansion years (2014-2016), is a vector of PUMA level demographic controls, denotes PUMA fixed effects, and denotes year fixed effects. Note that and have not been included in the model individually, as they will be absorbed by the PUMA fixed effects and year fixed effects, respectively. Standard errors will be heteroskedasticity-robust and clustered at the state level. In order to obtain causal identification, this model relies on the assumption that Medicaid expanding states and non-expanding states are on the same trends in outcomes over time (parallel trends assumption). One benefit of this model is its ease of interpretation: assuming internal validity, the treatment effect of expanding Medicaid is given, simply, by.

Unfortunately, as previously mentioned, this DiD model is far from ideal. To improve on the DiD specification, and to examine the effect of the non-Medicaid ACA provisions, I estimate a difference-in-difference-differences /dose response (DiDiD) specification, of the following form:

where is the 2013 uninsured rate for PUMA *a*, and denotes state-by-year fixed effects. As in the DiD model, some terms have been absorbed by the fixed effects and have not been included in the model individually: the PUMA fixed effects () have absorbed , , and , while the state-by-year fixed effects have absorbed and . Standard errors, again, will be heteroskedasticity-robust and clustered at the state level. The dose response moniker refers to the fact that areas are differentially affected by the Medicaid expansion due to different pre-treatment uninsured rates, meaning that PUMAs with higher pre-treatment uninsured rates get a large “dose” of Medicaid expansion, than PUMAs with low pre-treatment uninsured rates.

The identifying assumption of the DiDiD model for the effect of the Medicaid expansion, weaker than under the DiD, is that any factors differentially affecting labor market outcomes of expansion and non-expansion states are not correlated with pre-treatment uninsured rates (DiDiD parallel trends). The addition of the state-by year fixed effects which is made possible by the DiDiD specification controls for many factors that could plausibly bias the estimate in the DiD model such as the aforementioned state-level economic conditions or population growth. Adding the dose response variable (), which is continuous and measured at the PUMA level, provides many more observations (n = 762 PUMAs), as well as variation in treatment intensity (more identifying variation). All of this should lead to a more precise estimate that is closer to the true effect. Unfortunately, this model is not as easy to interpret as the DiD. The estimates produced by the DiDiD model are for theoretical PUMA with 100% uninsured. The treatment effect must therefore be scaled by the pre-treatment uninsured rates. Assuming internal validity, the effect for the average PUMA in this model (of the ACA Medicaid expansion) is given by . This estimate could also be scaled by the minimum or maximum pre-expansion uninsured rate to provide lower and upper bounds on the effect, respectively.

For the effect of the non-Medicaid ACA provisions ie. the effect of the 2014 ACA rollout in non-expanding states, the identifying assumption is that trends in labor market outcomes would not have varied differentially by pre-treatment PUMA uninsured rates. Assuming this holds, the effect for the average PUMA is given by . Note that this effect & its identifying assumption are akin to a DiD/dose response model where is the independent variable of interest. After estimating the Medicaid and non-Medicaid effect, I combine them to estimate the full effect of the 2014 ACA rollout including the Medicaid expansion (the effect of the 2014 ACA rollout in expanding states). This “Full ACA” effect, calculated for the average PUMA, is given by .

To provide evidence for/against the parallel trend assumptions, I perform a falsification test for differential pre-trends in labor market outcomes by estimating an event study model for both of my main specifications.

DiD (1) event study:

DiDiD (2) event study:

where , , , , and are indicators for each year, and 2013 (the year prior to the policy rollout) serves as the reference year. The falsification test for differential pre-trends, informally, is a test of whether the “treatment” effect is non-zero in the pre-expansion years ie. if the “treatment” effect is non-zero before the treatment has happened, something strange is happening, and parallel trends is violated. More formally, the test is whether and are significantly different from zero for the DiD specification. For the DiDiD specification, the test is whether and are significant (for the non-Medicaid effect), and whether and are significant (for the Medicaid expansion effect). If any of these coefficient estimates come up significant, the respective parallel trends assumption is violated. As these are falsification tests, note that a null result does not *prove* that the identifying assumptions hold, but rather there is insufficient evidence to conclude that they are violated. One additional useful characteristic of the event study models, is that they estimate treatment effects by year. This aspect allows a more nuanced analysis, ie. how the treatment effects evolve over time. This would allow the detection of a transitory effect in the first year, as was found by Peng et al. (2018). I examine event study estimates and determine if they tell a more complex story than the main specifications.

Recall that health insurance coverage gains were especially pronounced among certain demographic groups. I therefore perform heterogeneity analysis by re-estimating equation (2) for several demographic groups. I calculate DiDiD estimates by gender, college education, age, and race in order to see if labor supply of these groups is differentially affected by the ACA, as well as to preliminarily explore the robustness of my full sample estimates.

1. **Results**

Table 2 presents the results of estimating my main specifications, (1) & (2), on my full sample. Estimates for the DiD model are all very small (near zero), insignificant and positive. These results are consistent with previous studies outlined above. Indeed, Kaestner et al. (2017) note that most of their estimates were small, insignificant and positive. Table A1 (appendix) presents the results of estimating the DiD event study model. All pre-treatment year coefficient estimates are statistically insignificant, meaning that this model has “passed” the falsification test for differential pre-trends, although this doesn’t necessarily mean the estimates are internally valid. In general, estimates of the Medicaid expansion by year from this event study model do not tell a different story than the DiD estimates: all are near zero, and insignificant. Now that I have established a baseline of results consistent with prior literature, I am ready to move on to the DiDiD estimates.

As the estimates from the DiDiD are more difficult to interpret that the simple DiD estimates, I include the implied effects for the average PUMA in table 2. I do this for the Medicaid expansion effect, the non-Medicaid effect, and the “Full ACA” effect. Most DiDiD estimates are small and insignificant, with a key exception: the estimate of the non-Medicaid ACA effect on employment of 0.05 is sizable, significant and positive. This implies that the 2014 rollout of the non-Medicaid ACA provisions is associated with an increase in employment of 1.1 percentage points for the average PUMA. Additionally, this effect ranges from 0.2 percentage points (for the minimum uninsured PUMA) to 2.6 percentage points (for the maximum uninsured PUMA).

Table 3 presents the results of estimating the DiDiD event study model on my main sample. Note that none of the pre-expansion year estimates are statistically significant at conventional levels, meaning that neither the Medicaid effect nor the non-Medicaid effect failed the falsification test for parallel trends for any of my four outcome variables. Upon examining treatment effects by year for the non-Medicaid employment effect, my prior is more or less confirmed. It can be seen in the table, that the coefficient estimate for the non-Medicaid ACA effect on employment is essentially zero in the pre-treatment years, jumps to nearly 5 percentage points in 2014 (one year after rollout), and is about 6 percentage points in 2015 & 2016. Estimates for 2014-2016 are all statistically significant at the 5% level.

Also, note that there is a positive estimate of the effect of the Medicaid expansion on hours worked in 2014 significant at the 10% level. However, this estimate, at 1.28, is not very large in magnitude: this implies only a 0.27 hour (~ 16 minutes) increase in hours worked for the average PUMA, or 0.66 (~ 40 minutes) for the maximum uninsured rate. It seems possible that this significant estimate is the result of mere chance. This estimate is the only one in the table besides the non-Medicaid employment effect that is significant. Out of these 30 estimates, three of them should be significant at the 10% level due to mere chance. In addition, the estimate for 2012 is already ~ 1, and the coefficients for 2015 & 2016 are insignificant and negative.

Finally, the estimate for the Medicaid effect on wages in 2016 is sizable and nearing conventional significance levels. However, given that the estimates of this effect in other years are all over the place, and have large standard errors, I have a difficult time believing this estimate.

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| **Table 2: Full Sample Estimates** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| **DiD** |  |  |  |  |
| Medicaid x Post | 0.000441 | 0.00101 | 0.00145 | 0.00236 |
|  | (0.0050) | (0.0012) | (0.0036) | (0.0646) |
| **DiDiD** |  |  |  |  |
| Uninsured x Post | -0.00789 | -0.0108 | 0.0501\*\* | 0.598 |
|  | (0.0202) | (0.0131) | (0.0195) | (0.4769) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | -0.0243 | -0.0111 | -0.00586 | -0.452 |
|  | (0.0280) | (0.0235) | (0.0236) | (0.6089) |
|  |  |  |  |  |
| N | 54858 | 54863 | 54859 | 54859 |
|  |  |  |  |  |
| **Implied effects of ACA at mean pre-expansion uninsured rate** | | | |  |
|  |  |  |  |  |
| ACA without Medicaid expansion | -0.0015 | -0.0023 | 0.011 | 0.13 |
|  |  |  |  |  |
| Medicaid expansion | -0.0050 | -0.002 | -0.001 | -0.10 |
|  |  |  |  |  |
| Full ACA | -0.007 | -0.005 | 0.009 | 0.03 |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| --- | --- | --- | --- | --- |
| **Table 3: DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
|  |  |  |  |  |
| Uninsured x 2011 | 0.0822 | 0.0166 | 0.00157 | -0.155 |
|  | (0.0513) | (0.0275) | (0.0171) | (0.5777) |
|  |  |  |  |  |
| Uninsured x 2012 | 0.00515 | 0.00971 | 0.0138 | -0.704 |
|  | (0.0495) | (0.0163) | (0.0207) | (0.6121) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0411 | -0.00574 | 0.0466\*\* | -0.243 |
|  | (0.0474) | (0.0319) | (0.0177) | (0.4716) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.0315 | 0.0169 | 0.0613\*\*\* | 0.732 |
|  | (0.0568) | (0.0375) | (0.0215) | (0.7569) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.00894 | -0.0172 | 0.0579\*\* | 0.446 |
|  | (0.0325) | (0.0159) | (0.0243) | (0.9026) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | -0.0704 | -0.0123 | -0.000701 | 0.454 |
|  | (0.0640) | (0.0389) | (0.0197) | (0.6816) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | -0.0107 | -0.00817 | -0.0250 | 1.018 |
|  | (0.0645) | (0.0270) | (0.0262) | (0.7426) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | -0.0507 | -0.0106 | -0.0253 | 1.275\* |
|  | (0.0642) | (0.0356) | (0.0198) | (0.6612) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.0302 | -0.0345 | -0.0228 | -0.344 |
|  | (0.0646) | (0.0438) | (0.0237) | (0.8230) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.0731 | -0.00885 | 0.00476 | -0.816 |
|  | (0.0593) | (0.0350) | (0.0321) | (1.0478) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

Tables 4a & 4b present the results of my heterogeneity analysis. I re-estimate my DiDiD specification for eight demographic groups separately: males & females, individuals with no college education & individuals with some college education or more, ages 25-45 & ages 45-55, whites & non-whites. While I originally estimated ages 25-35 separately from ages 35-45, the results were not notably different, so I combined them into one category. Event study estimates for my heterogeneity analysis are reported in appendix tables A2-A9.

The first thing to note from the heterogeneity results is the remarkable consistency of the positive effect of the non-Medicaid provisions on employment. As can be seen from the tables, all but one of these coefficient estimates are in the range of ~4-6 percentage points (main results estimate was 0.5), and all but two are statistically significant at (at least) the 10% level. This gives me greater confidence in the main sample estimate of the non-Medicaid ACA effect on employment.

Additionally, note that the Medicaid expansion seems to be associated with a modest decrease in labor supply for females. The estimates for females on hours worked, labor force participation, and wages are all negative, of non-trivial magnitude, and nearing statistical significance (|t-stats| > 1).

Finally note that some the coefficient estimates for wages are of substantial magnitude, most notably the Medicaid effect for individuals with some college education. However, upon examining this effects’ event study estimates (table A5), it can be seen that parallel trends is violated, and the estimate is not to be believed. Event study estimates for other sizable estimates of the Medicaid effect on wages look similar to that of the no college education event study. Also note that some of the estimates of the non-Medicaid effect on wages are sizable. However, these estimates (and their respective event study estimates) vary wildly in magnitude, sign and statistical significance, leading me to distrust them.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 4a: Heterogeneity Results** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| **Males** |  |  |  |  |
| Uninsured x Post | -0.00382 | -0.0126 | 0.0424\*\* | 0.546 |
|  | (0.0314) | (0.0153) | (0.0171) | (0.3333) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | -0.0130 | 0.0208 | -0.00771 | 0.225 |
|  | (0.0368) | (0.0205) | (0.0206) | (0.7319) |
| **Females** |  |  |  |  |
| Uninsured x Post | -0.0104 | -0.00264 | 0.0586\*\* | 0.592 |
|  | (0.0344) | (0.0276) | (0.0233) | (0.8255) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | -0.0442 | -0.0464 | -0.00416 | -1.182 |
|  | (0.0432) | (0.0389) | (0.0319) | (0.9391) |
| **No College Education** |  |  |  |  |
| Uninsured x Post | 0.0417 | -0.0136 | 0.0594\*\* | 0.112 |
|  | (0.0293) | (0.0244) | (0.0236) | (0.5399) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | 0.0393 | -0.0122 | -0.0237 | 0.0129 |
|  | (0.0453) | (0.0423) | (0.0304) | (0.7217) |
| **Some College or More** |  |  |  |  |
| Uninsured x Post | -0.0458 | -0.00807 | 0.0422\* | 1.237\* |
|  | (0.0281) | (0.0229) | (0.0221) | (0.7013) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | -0.0749\*\* | -0.00925 | 0.0145 | -0.857 |
|  | (0.0315) | (0.0240) | (0.0248) | (0.8248) |
| **Ages 25-45** |  |  |  |  |
| Uninsured x Post | -0.0573 | -0.00724 | 0.0488\* | 0.574 |
|  | (0.0379) | (0.0151) | (0.0211) | (0.5981) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | 0.0280 | -0.0137 | -0.0130 | -1.058 |
|  | (0.0467) | (0.0265) | (0.0266) | (0.7155) |
| **Ages 45-55** |  |  |  |  |
| Uninsured x Post | 0.0509 | -0.0172 | 0.0491\*\* | 0.441 |
|  | (0.0401) | (0.0166) | (0.0184) | (0.5789) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | -0.0874 | -0.00397 | 0.0127 | 1.013 |
|  | (0.0518) | (0.0271) | (0.0222) | (0.9322) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 4b: Heterogeneity Results Continued** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| **Non-White** |  |  |  |  |
| Uninsured x Post | 0.0597 | -0.00614 | 0.0460\*\* | 1.366\* |
|  | (0.0496) | (0.0236) | (0.0209) | (0.7194) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | -0.0719 | 0.0111 | 0.00225 | -0.577 |
|  | (0.0639) | (0.0310) | (0.0274) | (1.0100) |
| **White** |  |  |  |  |
| Uninsured x Post | -0.0535 | -0.0136 | 0.0338\*\* | 0.0146 |
|  | (0.0457) | (0.0203) | (0.0143) | (0.5615) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | 0.0862 | -0.0105 | -0.0306 | 0.341 |
|  | (0.0626) | (0.0282) | (0.0261) | (0.7497) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

1. **Robustness Checks**

In order to test the strength of my results, I perform two robustness checks. Tables 5 and 6 present the results of re-estimating the DiDiD model and its event study on the main sample with two additional pre-years (2009 & 2010) of data added in. I examine how well the DiDiD estimates match up with my main results, and utilize the event study primarily as a further test of parallel trends, as there are now four pre-treatment years to examine.

The estimate of the non-Medicaid effect on employment has decreased in magnitude slightly, but taken together with the event study estimates, these estimates are quite consistent with my main results. One notable difference here is the negative and statistically significant estimate of the non-Medicaid effect on labor force participation of (-0.299). This implies that the non-Medicaid ACA provisions are associate with a decrease of 0.6% for the average PUMA, or up to a 1.5% decrease for the maximum uninsured PUMA. The event study estimates for this effect look pretty good. Only the estimate for 2009 is significant, and the estimates for 2011 & 2012 are not only insignificant, but near-zero. This modest decrease in labor force participation associated with the non-Medicaid ACA provisions is consistent with the effect found by Duggan et al. (2017)

The estimate for the Medicaid effect on wages is again, sizable and nearing statistical significance. Looking at the event study, the coefficient estimates are far more consistent in the post treatment years (~ 5-6%), although standard errors are quite large.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 5: 2009-2016 Sample - DiDiD Estimates** | | | | |
|  | ln(wage) | Labor Force Participation | Employed | Usual Hours Worked |
| **DiDiD** |  |  |  |  |
| Uninsured x Post | -0.0269 | -0.0299\*\* | 0.0435\* | 0.218 |
|  | (0.0177) | (0.0118) | (0.0216) | (0.3790) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | -0.0409 | 0.00224 | -0.0162 | -0.499 |
|  | (0.0276) | (0.0209) | (0.0255) | (0.5233) |
|  |  |  |  |  |
| N | 73145 | 73151 | 73147 | 73147 |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 6: 2009-2016 DiDiD Event Study** | | | | |
|  | ln(wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2009 | 0.0697 | 0.0526\*\* | 0.0307 | 0.977\* |
|  | (0.0569) | (0.0223) | (0.0220) | (0.5416) |
|  |  |  |  |  |
| Uninsured x 2010 | 0.113\*\* | 0.0310 | 0.0124 | -0.315 |
|  | (0.0477) | (0.0223) | (0.0205) | (0.8384) |
|  |  |  |  |  |
| Uninsured x 2011 | 0.0937\* | 0.00931 | -0.0000014 | -0.361 |
|  | (0.0466) | (0.0279) | (0.0181) | (0.6074) |
|  |  |  |  |  |
| Uninsured x 2012 | 0.00617 | 0.00165 | 0.0105 | -0.834 |
|  | (0.0472) | (0.0159) | (0.0231) | (0.6769) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0501 | -0.0212 | 0.0487\*\* | -0.438 |
|  | (0.0429) | (0.0322) | (0.0181) | (0.4788) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.0510 | 0.0137 | 0.0620\*\*\* | 0.534 |
|  | (0.0533) | (0.0390) | (0.0202) | (0.7023) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.0120 | -0.0256 | 0.0520\*\* | 0.238 |
|  | (0.0331) | (0.0196) | (0.0213) | (0.8817) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2009 | 0.00299 | -0.0516 | 0.0240 | 0.207 |
|  | (0.0633) | (0.0325) | (0.0269) | (0.6961) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2010 | 0.000906 | -0.00774 | 0.0141 | 1.497 |
|  | (0.0688) | (0.0271) | (0.0237) | (0.9147) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | -0.0718 | -0.00233 | 0.00197 | 0.772 |
|  | (0.0603) | (0.0410) | (0.0220) | (0.6932) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | 0.000455 | 0.000476 | -0.0169 | 1.176 |
|  | (0.0615) | (0.0255) | (0.0273) | (0.7937) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | -0.0602 | 0.00305 | -0.0260 | 1.510\*\* |
|  | (0.0599) | (0.0356) | (0.0209) | (0.6496) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.0499 | -0.0325 | -0.0221 | -0.220 |
|  | (0.0624) | (0.0459) | (0.0224) | (0.7927) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.0531 | -0.000547 | 0.0134 | -0.597 |
|  | (0.0618) | (0.0384) | (0.0307) | (1.0427) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

In order to verify that any estimated effects are not a result of some confounding event, concurrent with the 2014 ACA rollout and Medicaid expansion, I conduct a placebo test by estimating my main specification (2) on seniors. Given that seniors (age 65+) all have access to public health insurance already (Medicare) it is hard to imagine that they would be substantially affected by an expansion of public or private health insurance. Therefore, estimates for seniors should be zero/insignificant. If not, I am likely detecting a confounding event. Table 7 presents DiDiD estimates for seniors. All estimates are near-zero and insignificant, with the exception of the estimates on wages. Although these coefficients are sizable in magnitude, they are insignificant and the opposite sign from many of my main sample & heterogeneity estimates, suggesting that they are likely just noise. Even the estimate of the non-Medicaid effect on wages, which is the largest in magnitude and the closest to statistical significance, mostly fails the parallel trends falsification test (see table A10). These results are more or less in line with expectations (null results) and give me some confidence that I am not detecting a confounding event.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 7: Robustness Test - Estimates for Seniors (65+)** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| **DiDiD** |  |  |  |  |
| Uninsured x Post | -0.256 | 0.00166 | 0.0373 | -0.273 |
|  | (0.2101) | (0.0107) | (0.0435) | (2.1462) |
|  |  |  |  |  |
| Medicaid x Uninsured x Post | 0.206 | 0.000127 | -0.0259 | 0.722 |
|  | (0.2307) | (0.0211) | (0.0480) | (2.6735) |
|  |  |  |  |  |
| N | 47148 | 72570 | 47224 | 49811 |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

1. **Conclusion/Discussion**

In summation, the Affordable Care Act is the most significant change to U.S National health policy in recent history. Several studies have attempted to estimate the effects of this sweeping reform on labor supply by studying the 2014 rollout of many of its key provisions, including the Medicaid expansion.

One of the goals of this paper was to determine whether the null results of previous studies on the effects of the ACA Medicaid expansion were truly null results, or merely type II error/a lack of statistical power due to a lack of much identifying variation. By utilizing the Difference-in-Difference-in-Differences model to leverage pre-treatment uninsured rates in local areas and provide more identifying variation, I provided additional suggestive evidence that the 2014 Medicaid expansion was not associated with substantial effects on labor supply, possibly with the exception of wages. However, with regard to wages, there is not a clear explanation as to why the Medicaid expansion would be associated with a decrease in wages, especially given that I find no significant effects on hours worked. Given that these estimates were highly variable and not statistically significant, I am not confident in them. More investigation that is beyond the scope of this paper would be required to determine the veracity of these estimates.

The other primary goal of this paper was to estimate the effects of the non-Medicaid ACA provisions, rolled out in 2014, on labor supply. The only clear, significant estimate of substantial magnitude is that of the non-Medicaid provisions on employment: this estimate of 0.0501 (from my main results) implies that the 2014 rollout of the individual mandate, insurance regulations, and insurance exchanges with subsidies is associated with an increase in employment of 1.1 percentage points for the average PUMA, an increase in employment of 0.2 percentage points for the minimum uninsured PUMA, and an increase in employment of 2.6 percentage points for the maximum uninsured PUMA. Looking across my main results, heterogeneity results, robustness checks, and associated event study results, this effect on employment seems to be fairly robust.

This seems to fit with the “job lock” story outlined earlier. While the insurance exchanges (and associated subsidies) and the Medicaid expansion were intended to reduce the link between employment and health insurance, these provisions did not apply to everyone: the subsidies only applied to individuals with incomes below 400% of the federal poverty line, and the Medicaid expansion applied to individuals below 138% of the federal poverty line. Additionally, the individual mandate and insurance regulations took effect in 2014, and the employer mandate took effect in 2015. Given the requirement to have insurance, the fact that private insurance improved due to the new regulations, and the increased prevalence of employer provided insurance from 2015 on, it could be that many individuals still saw employer provided health insurance as their best option for obtaining health coverage, and became more reluctant to leave jobs with said health insurance benefits.

The only other notable estimates are that of the modest (but insignificant) estimates of the Medicaid expansion on female labor supply (labor force participation, hours worked, wages) and the estimated decrease in labor force participation associated with the Medicaid expansion. The estimates for Medicaid and female labor supply are nearing significance and show up across three of four outcome variables. This could possibly be driven by married women, who are likely to be secondary earners in a household. Indeed, Currie & Madrian note that married women are particularly less likely to be employed if there is a source of health insurance available that is not tied to employment. Finally, the estimated modest decrease in labor supply associated with the non-Medicaid provisions from the 2009-2016 sample is interesting. While I do not have a good way of probing the robustness of this estimate, this estimate is consistent with the results of Duggan et al. (2017) which attributes this estimated effect to the health insurance exchanges. Indeed, this is consistent with the CBO’s projections that the insurance exchange subsidies would reduce labor supply due to increased effective marginal tax rates of income (the subsidies phase out as one nears the eligibility threshold.

It is important to note that the ACA, due to the sweeping nature of the reform, is quite the blunt instrument. This means that any estimated effects are not necessarily applicable to other contexts. To improve upon this analysis, there are a few key directions to take it. I would like to be able to estimate a model with PUMA specific linear trends, but this requires significant computational power I did not have access to. This was also the case for running individual level regressions, which would be preferable to aggregate analysis because it would allow the use of individual level controls. Future work could additionally include late-expanding states by coding the treatment variable by year, although this would require more years of data to get good estimates. Finally, it would be interesting to perform more heterogeneity analysis on the basis of number of children, income & marital status, given that these were some the groups whose health coverage increased the most due to the ACA.

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**Appendix**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table A1: Full Sample DiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
|  |  |  |  |  |
| Medicaid x 2011 | 0.000337 | -0.00295 | 0.000400 | -0.108 |
|  | (0.0053) | (0.0020) | (0.0025) | (0.0822) |
|  |  |  |  |  |
| Medicaid x 2012 | 0.000388 | -0.000124 | 0.00125 | -0.0238 |
|  | (0.0034) | (0.0020) | (0.0022) | (0.0640) |
|  |  |  |  |  |
| Medicaid x 2014 | -0.00380 | 0.00104 | 0.000207 | -0.0823 |
|  | (0.0046) | (0.0017) | (0.0017) | (0.0580) |
|  |  |  |  |  |
| Medicaid x 2015 | -0.00188 | -0.00294 | 0.00260 | -0.0943 |
|  | (0.0048) | (0.0020) | (0.0027) | (0.0612) |
|  |  |  |  |  |
| Medicaid x 2016 | 0.00773 | 0.00185 | 0.00319 | 0.0519 |
|  | (0.0064) | (0.0017) | (0.0041) | (0.1046) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table A2: Males DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.0448 | -0.00416 | -0.00122 | -0.841 |
|  | (0.0532) | (0.0406) | (0.0263) | (0.7358) |
|  |  |  |  |  |
| Uninsured x 2012 | -0.00674 | -0.0220 | 0.0281 | -1.983\*\*\* |
|  | (0.0795) | (0.0228) | (0.0200) | (0.7162) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.00542 | -0.00733 | 0.0476\*\*\* | -0.988 |
|  | (0.0665) | (0.0368) | (0.0149) | (0.7144) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.00332 | -0.0123 | 0.0554\*\*\* | -0.304 |
|  | (0.0391) | (0.0305) | (0.0182) | (0.5731) |
|  |  |  |  |  |
| Uninsured x 2016 | 0.0178 | -0.0442 | 0.0511\*\* | 0.105 |
|  | (0.0622) | (0.0325) | (0.0226) | (0.5624) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | 0.00136 | -0.0124 | 0.0131 | 1.555 |
|  | (0.0723) | (0.0464) | (0.0345) | (1.0178) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | 0.0150 | 0.0190 | -0.0419 | 2.087\*\* |
|  | (0.0834) | (0.0277) | (0.0287) | (0.9719) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | 0.00961 | 0.00806 | -0.0311 | 2.707\*\* |
|  | (0.0794) | (0.0386) | (0.0203) | (1.2682) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.0114 | 0.0120 | -0.0158 | 1.094 |
|  | (0.0466) | (0.0378) | (0.0252) | (0.8356) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.0210 | 0.0490 | -0.00503 | 0.516 |
|  | (0.0796) | (0.0426) | (0.0266) | (1.0907) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table A3: Females DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.107 | 0.0256 | 0.00189 | 0.297 |
|  | (0.0727) | (0.0264) | (0.0207) | (0.6261) |
|  |  |  |  |  |
| Uninsured x 2012 | 0.0234 | 0.0446 | -0.000592 | 0.671 |
|  | (0.0456) | (0.0315) | (0.0313) | (0.8058) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0752 | -0.00307 | 0.0457 | 0.389 |
|  | (0.0499) | (0.0445) | (0.0354) | (0.9071) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.0548 | 0.0484 | 0.0671\*\* | 1.552 |
|  | (0.1002) | (0.0582) | (0.0303) | (1.3582) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.0311 | 0.0168 | 0.0644\*\* | 0.801 |
|  | (0.0548) | (0.0332) | (0.0314) | (1.5208) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | -0.120 | 0.00157 | -0.0134 | -0.275 |
|  | (0.0912) | (0.0453) | (0.0292) | (1.0283) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | -0.0337 | -0.0354 | -0.00900 | -0.0666 |
|  | (0.0819) | (0.0446) | (0.0351) | (0.9022) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | -0.112 | -0.0334 | -0.0211 | -0.0587 |
|  | (0.0719) | (0.0519) | (0.0412) | (1.2565) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.0477 | -0.0814 | -0.0306 | -1.667 |
|  | (0.1133) | (0.0648) | (0.0445) | (1.4465) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.127 | -0.0583 | 0.0168 | -2.163 |
|  | (0.0866) | (0.0482) | (0.0471) | (1.6559) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| **Table A4: No College DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.0375 | -0.00381 | 0.00123 | -0.178 |
|  | (0.0739) | (0.0344) | (0.0322) | (1.3869) |
|  |  |  |  |  |
| Uninsured x 2012 | -0.0468 | -0.0268 | 0.0279 | -0.195 |
|  | (0.0790) | (0.0212) | (0.0409) | (0.8606) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0525 | -0.0580 | 0.0505\*\* | -0.562 |
|  | (0.0450) | (0.0425) | (0.0193) | (1.1194) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.0115 | -0.00767 | 0.0860\*\* | -0.304 |
|  | (0.0819) | (0.0368) | (0.0376) | (1.3489) |
|  |  |  |  |  |
| Uninsured x 2016 | 0.0518 | -0.00595 | 0.0709\*\* | 0.826 |
|  | (0.0411) | (0.0422) | (0.0311) | (1.1817) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | -0.0191 | 0.00562 | -0.00218 | -0.478 |
|  | (0.0914) | (0.0565) | (0.0392) | (1.5201) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | 0.0784 | 0.0188 | -0.0523 | 0.387 |
|  | (0.1052) | (0.0410) | (0.0474) | (1.0820) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | 0.0439 | 0.0438 | -0.0436 | 1.311 |
|  | (0.0958) | (0.0510) | (0.0265) | (1.3365) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | 0.132 | -0.0115 | -0.0716 | 0.325 |
|  | (0.0966) | (0.0545) | (0.0445) | (1.3831) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | 0.00128 | -0.0446 | -0.0103 | -1.689 |
|  | (0.0939) | (0.0619) | (0.0501) | (1.3563) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| **Table A5: College DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.125\*\* | 0.0405 | 0.00246 | -0.0700 |
|  | (0.0531) | (0.0265) | (0.0119) | (0.8937) |
|  |  |  |  |  |
| Uninsured x 2012 | 0.0763\* | 0.0469 | -0.00146 | -1.051 |
|  | (0.0425) | (0.0331) | (0.0121) | (0.6851) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0402 | 0.0484 | 0.0420\* | 0.249 |
|  | (0.0625) | (0.0312) | (0.0240) | (1.1398) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.0799 | 0.0401 | 0.0394 | 2.037\*\* |
|  | (0.0570) | (0.0558) | (0.0244) | (0.7811) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.0560 | -0.0253 | 0.0462\* | 0.303 |
|  | (0.0409) | (0.0294) | (0.0267) | (1.2925) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | -0.116\* | -0.0396 | -0.00127 | 1.188 |
|  | (0.0636) | (0.0313) | (0.0188) | (1.0281) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | -0.102\* | -0.0444 | 0.00190 | 1.439\* |
|  | (0.0581) | (0.0377) | (0.0205) | (0.7807) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | -0.138\*\* | -0.0680\*\* | -0.00479 | 1.082 |
|  | (0.0657) | (0.0330) | (0.0261) | (1.2179) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.188\*\*\* | -0.0631 | 0.0246 | -1.133 |
|  | (0.0654) | (0.0577) | (0.0261) | (0.9053) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.118\*\* | 0.0193 | 0.0242 | 0.103 |
|  | (0.0488) | (0.0358) | (0.0288) | (1.4535) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| **Table A6: Ages 25-45 DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.0631 | 0.00718 | -0.00199 | 0.562 |
|  | (0.0650) | (0.0211) | (0.0187) | (0.8129) |
|  |  |  |  |  |
| Uninsured x 2012 | 0.0151 | -0.00145 | 0.0119 | -0.322 |
|  | (0.0778) | (0.0218) | (0.0327) | (0.4553) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.00242 | -0.0174 | 0.0439\* | -0.342 |
|  | (0.0853) | (0.0361) | (0.0233) | (0.8611) |
|  |  |  |  |  |
| Uninsured x 2015 | -0.0220 | 0.0135 | 0.0582\*\* | 1.489 |
|  | (0.0783) | (0.0358) | (0.0267) | (1.1394) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.0741 | -0.0121 | 0.0543\* | 0.812 |
|  | (0.0647) | (0.0213) | (0.0319) | (1.2135) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | -0.102 | 0.0108 | 0.00339 | -0.520 |
|  | (0.0783) | (0.0357) | (0.0221) | (0.9482) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | -0.0672 | -0.00934 | -0.0285 | 0.417 |
|  | (0.0870) | (0.0348) | (0.0369) | (0.6098) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | -0.0369 | 0.0119 | -0.0412 | 1.146 |
|  | (0.1050) | (0.0429) | (0.0265) | (1.0585) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.0154 | -0.0351 | -0.0342 | -2.031\* |
|  | (0.0862) | (0.0449) | (0.0297) | (1.1809) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.0327 | -0.0163 | 0.0115 | -2.396\* |
|  | (0.0777) | (0.0373) | (0.0396) | (1.3997) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| **Table A7: Ages 45-55 DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.0869 | 0.0336 | 0.00720 | -1.737\* |
|  | (0.0783) | (0.0445) | (0.0256) | (0.8708) |
|  |  |  |  |  |
| Uninsured x 2012 | -0.0449 | 0.0301 | 0.0139 | -1.632 |
|  | (0.0840) | (0.0300) | (0.0222) | (1.2227) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0768 | 0.0159 | 0.0455\*\* | -0.296 |
|  | (0.0583) | (0.0302) | (0.0195) | (1.0924) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.0687 | 0.0203 | 0.0628\*\*\* | -1.150 |
|  | (0.0771) | (0.0470) | (0.0220) | (1.0618) |
|  |  |  |  |  |
| Uninsured x 2016 | 0.0492 | -0.0241 | 0.0602\*\* | -0.599 |
|  | (0.0685) | (0.0296) | (0.0226) | (0.6245) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | -0.0518 | -0.0621 | -0.0120 | 2.113\* |
|  | (0.0869) | (0.0587) | (0.0273) | (1.1050) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | 0.0530 | -0.00619 | -0.0215 | 1.957 |
|  | (0.0975) | (0.0375) | (0.0285) | (1.3504) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | -0.0652 | -0.0540 | 0.0107 | 1.659 |
|  | (0.0725) | (0.0371) | (0.0255) | (1.2204) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.0468 | -0.0305 | 0.0000916 | 3.095\*\* |
|  | (0.0840) | (0.0547) | (0.0244) | (1.2123) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.149\* | 0.00414 | -0.00635 | 2.352\*\* |
|  | (0.0852) | (0.0526) | (0.0283) | (1.0604) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| **Table A8: Non-Whites DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.0577 | 0.0163 | -0.0597 | -3.469 |
|  | (0.0939) | (0.0489) | (0.0389) | (2.4236) |
|  |  |  |  |  |
| Uninsured x 2012 | 0.00225 | 0.00565 | -0.0501\*\* | -2.390 |
|  | (0.1033) | (0.0377) | (0.0207) | (1.6677) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0599 | -0.0109 | -0.00189 | -0.753 |
|  | (0.1185) | (0.0578) | (0.0223) | (1.5286) |
|  |  |  |  |  |
| Uninsured x 2015 | 0.193 | -0.0123 | 0.0195 | -0.536 |
|  | (0.1220) | (0.0564) | (0.0288) | (1.7374) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.0134 | 0.0267 | 0.0105 | -0.482 |
|  | (0.0468) | (0.0334) | (0.0244) | (1.5675) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | 0.0462 | 0.00747 | 0.0913\* | 4.374\* |
|  | (0.1235) | (0.0616) | (0.0509) | (2.5530) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | 0.0163 | 0.00764 | 0.0600 | 3.519\* |
|  | (0.1216) | (0.0431) | (0.0403) | (1.7714) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | 0.0257 | 0.0218 | 0.0603 | 3.199 |
|  | (0.1318) | (0.0612) | (0.0369) | (2.0001) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | -0.167 | 0.0185 | 0.0387 | 1.316 |
|  | (0.1488) | (0.0664) | (0.0418) | (1.9513) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | -0.0127 | 0.00830 | 0.0592 | 1.658 |
|  | (0.0995) | (0.0546) | (0.0396) | (1.9483) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| **Table A9: Whites DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
| Uninsured x 2011 | 0.0379 | -0.0533\*\* | 0.0361\* | 1.023 |
|  | (0.0932) | (0.0226) | (0.0212) | (1.2153) |
|  |  |  |  |  |
| Uninsured x 2012 | -0.0403 | -0.0209 | 0.0103 | 1.687 |
|  | (0.0630) | (0.0231) | (0.0316) | (1.7930) |
|  |  |  |  |  |
| Uninsured x 2014 | 0.0115 | -0.0578\*\* | 0.0461 | -0.0230 |
|  | (0.0656) | (0.0236) | (0.0280) | (0.6948) |
|  |  |  |  |  |
| Uninsured x 2015 | -0.113 | -0.0167 | 0.0435\* | 2.211\*\*\* |
|  | (0.1054) | (0.0305) | (0.0223) | (0.7053) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.0614 | -0.0409\* | 0.0582\*\*\* | 0.568 |
|  | (0.0922) | (0.0236) | (0.0170) | (0.9672) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | 0.0554 | 0.0112 | -0.0185 | -3.089 |
|  | (0.1177) | (0.0520) | (0.0326) | (2.1561) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | 0.00587 | 0.0324 | -0.0505 | -2.223 |
|  | (0.0729) | (0.0414) | (0.0385) | (2.5156) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | -0.0219 | 0.0110 | -0.0800\*\* | -0.240 |
|  | (0.0848) | (0.0369) | (0.0357) | (1.9548) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | 0.258\*\* | 0.0146 | -0.0326 | -2.031\* |
|  | (0.1173) | (0.0476) | (0.0302) | (1.1392) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | 0.0810 | -0.0134 | -0.0489 | -2.034\* |
|  | (0.1022) | (0.0332) | (0.0423) | (1.1668) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level

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| **Table A10: Seniors - DiDiD Event Study** | | | | |
|  | ln(Wage) | Labor Force Participation | Employed | Usual Hours Worked |
|  |  |  |  |  |
| Uninsured x 2011 | -0.445\*\* | 0.0267 | 0.0204 | 8.687\*\* |
|  | (0.1800) | (0.0252) | (0.0472) | (3.8692) |
|  |  |  |  |  |
| Uninsured x 2012 | -0.238 | 0.0252 | -0.0402 | 2.757 |
|  | (0.2819) | (0.0400) | (0.0447) | (4.9165) |
|  |  |  |  |  |
| Uninsured x 2014 | -0.456\* | 0.0248 | -0.0130 | -0.162 |
|  | (0.2353) | (0.0231) | (0.0687) | (2.8599) |
|  |  |  |  |  |
| Uninsured x 2015 | -0.369 | 0.0178 | 0.0811 | 5.228 |
|  | (0.2383) | (0.0303) | (0.0528) | (6.1503) |
|  |  |  |  |  |
| Uninsured x 2016 | -0.621\*\*\* | 0.0143 | 0.0233 | 5.444 |
|  | (0.2143) | (0.0200) | (0.0619) | (4.8648) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2011 | 0.639\*\* | -0.0284 | -0.0876 | -8.085\* |
|  | (0.3117) | (0.0362) | (0.0647) | (4.5627) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2012 | -0.0346 | -0.0318 | -0.000000538 | -3.000 |
|  | (0.4300) | (0.0420) | (0.0530) | (5.3260) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2014 | 0.341 | -0.0159 | 0.0442 | -0.0318 |
|  | (0.2817) | (0.0393) | (0.0701) | (3.7663) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2015 | 0.348 | -0.0205 | -0.167\*\*\* | -3.367 |
|  | (0.3145) | (0.0394) | (0.0598) | (6.4340) |
|  |  |  |  |  |
| Medicaid x Uninsured x 2016 | 0.525 | -0.0236 | -0.0415 | -5.415 |
|  | (0.3144) | (0.0314) | (0.0660) | (5.3715) |

*Notes:* Standard errors, heteroskedasticity-robust and clustered at the state level, are in parentheses. \*\*\* Denotes statistical significance at 1 percent level, \*\* Denotes statistical significance at 5 percent level, \* Denotes statistical significance at 10 percent level