The Impact of the Affordable Care Act Dependent Care Provision on Long-term Young Adult Labor Market Choices

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Abstract

In 2010, the Affordable Care Act's Dependent Care Provision mandated that insurance companies allow children up to age 25 to their parents' employer-sponsored health insurance. Prior to 2010, many states had implemented similar dependent care mandates with varying eligibility requirements prior to the act. This paper analyzes the impact of these policies on labor market choices of young adults using difference-in-differences regression model. I look at several labor market outcomes, measuring the impact of the policy over time, as well as for different demographic groups.

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1 Introduction

1.1 Background

In this paper, I analyze the impacts of the Affordable Care Act's (ACA's) Dependent Care Provision on the labor market choices of young adults using a difference-in-differences regression model. The 2010 ACA Dependent Care Provision is a federal mandate that requires insurers to allow young adults to stay on their parents' employer-sponsored health insurance plans until age 26. Prior to the ACA mandate, 37 states had passed policies that extended the dependent eligibilty to above 19, but these laws had varying eligibility and age requirements (NCSL 2016). The age limits varied significantly by state from an age 19 cutoff to age an 29 cutoff. Some states additionally required the dependent to be in school, unmarried, or childless. However, the 2010 provision extended coverage eligibility nationally to all young adults under 26 whose parents have employer-sponsored health insurance.

The Dependent Care Provision is a policy aimed at increasing health insurance coverage rates among young adults. In the United States, young adults have historically had the highest uninsurance rates of the population. In 2020, young adults ages 19-34 had the highest uninsurance rate of any age group at 15.6 percent (U.S. Census Bureau). Known as the "young invincible" mindset, many choose to forego the purchase of health insurance because they believe they have low risk of high healthcare costs and health problems. While some young adults have employee-sponsored health insurance or qualify for government-sponsored insurance, others have to purchase health insurance on the open market. Although this policy was intended to reduce uninsurance of young adults 18-25, its effects may also spillover to young adults' labor market outcomes. I examine the relationship between dependent coverage and labor market outcomes in this study.

In this paper, I first identify the impact of the Dependent Care Provision on young adult health insurance coverage rates. After establishing that the provision increases young adult health insurance coverage rates, I look at how this increased coverage impacts young adult labor market choices and outcomes.

1.2 Research Question and Hypotheses

This paper aims to answer the following question. What is the impact of the Affordable Care Act (ACA) Dependent Care Provision on young adult labor-market outcomes? For health insurance outcomes, I look specifically at the overall coverage rate, private coverage rate, dependent coverage rate, and Medicaid coverage rate. For labor market outcomes, I look at the impacts on hours worked per week, weeks worked per year, employment rate, unemployment rate, not in the labor force (NILF) rate, self-employment rate, and annual income. I have developed hypotheses for how the provision will impact the dependent variables based on literature and economic theory.

Table 1 displays my hypotheses for how dependent coverage mandates and the ACA Dependent Care Provision, specifically, affect the health insurance coverage rates and labor market outcomes.

Table 1: Hypotheses

H1:	Dependent coverage eligibility increases insurance coverage rates for young adults.
H2:	Dependent coverage eligibility decreases employment rates for young adults.
H3:	Dependent coverage increases annual income for young adults.
H4:	Dependent coverage eligibility decreases the hours worked per week for young adults.
H5:	Dependent coverage eligibility decreases the weeks worked per year for young adults.
H6:	Dependent coverage eligibility increases the self-employment rate for young adults.
H7:	Dependent coverage eligibility increases the NILF rate for young adults.

2 Literature Review

2.1 Relevant Literature

There is an array of literature studying the various impacts of the ACA Dependent Care Provision on young adults, and a subset of literature analyzing how the provision affects young adult labor market outcomes. First, I will briefly review literature studying the healthcare-related effects of the ACA Dependent Care Provision. This literature supports a main assumption in my research— the Dependent Care Provision increases the health insurance coverage rate of young adults. Then, I will discuss the broader array of economics literature studying the impact of health insurance on labor-market outcomes. This will help me understand the various channels through which health insurance coverage can impact labor decisions. Finally, I will review literature focusing specifically on the labor-market outcomes of the Dependent Care Provision. This will give context about previous studies' data, methods, and controls as well as how my research can contribute to literature.

There is extensive literature identifying the effects of the Dependent Care Provision on young adult health insurance coverage, access to medical care, and health expenditures. Before 2010, approximately 30 percent of young adults were uninsured (CMS). Young adults ages 19 to 34 continue to have the highest rate of uninsurance in the United States at an average of 15.6 percent in 2019 (Conway 2020). However, research has found that the Dependent Care Provision lead to high take-up of parental insurance coverage, causing statistically significant reductions in young adult uninsurance and other forms of coverage (Antwi, Moriya, Simon 2013). A study found that the Dependent Care Provision also increased access to care, especially among young men, unmarried people and non-students (Sommers et al. 2013). The study used quarterly 2005-2011 panel data from the National Health Interview Survey (NHIS) and Annual Social and Economic Supplement (ASEC) to the U.S. Census Bureau's Current Population Survey (CPS). Additionally, a study found that the provision also decreased the percentage of young adults with out-of-pocket spending greater than $1,500 by a net of 2.4 percent (Busch, Golberstein, Meara 2014).

There is an array of literature studying the correlation between health insurance coverage and labor market outcomes. These studies measure the impact of health insurance coverage on outcomes such as job-lock (Cooper and Monheit 1993; Kapur 1998), self-employment (Madrian 2013) and wages (Kolstad and Kowalski 2016). While some of this literature focuses different sub-populations such as children and retirees, little literature has focused on young adults.

Multiple studies have looked specifically at the impact of the Dependent Care Provision on young adult labor-related outcomes using a difference-in-differences regression design. Heim, Lurie, and Simon analyze the impact of the ACA Dependent Care Provision on several labor market indicators including employment status, job characteristics and post-secondary education using a panel data of tax records from 2008-2013. They use a difference-in-differences regression model with young adults ages 24-25 as the treatment group, young adults ages 27-29 as the control age, and the 2010 mandate as the intervention. Unlike other studies, this data set allows them to match dependents to their parents using social security numbers from a 1997 tax data set. This allows them to narrow their sample to only young adults whose parents have employer-sponsored health insurance. This paper found some minor effects on labor outcomes, including that young adults were influenced to earn less annual income, be more likely to work for employers that offer fringe benefits, more likely to enroll as a full-time or graduate student, and more likely to be self-employed. However, this study found that the magnitude of these effects are very small compared to other estimates in literature.

Another study exploits the variation in state laws prior to the 2010 ACA that extended the age that young adults could qualify for dependent coverage under their parent's employer-sponsored health insurance plans (Depew 2015). This study found that the provision increased labor supply on the intensive margin not the extensive margin, meaning that there was an increase in the hours young adults worked per year. The study also uses a difference-in-differences model but uses states to identify the treatment and control group. States that implemented dependent care policies prior to 2010 were the treatment group, and states that did not were the control group. The study used panel data from the American Community Survey (ACS), Medical Expenditure Panel Survey (MEPS), and Survey of Income and Program Participation (SIPP). The study emphasizes the importance of a large sample size on the validity of the analysis, because the mandate has relatively small effects on labor market outcomes.

A study by Dillender investigates how dependent coverage under parent's employer-sponsored health insurance influences job-lock, educational decisions, and wages (Dillinder 2014). The study similarly uses the variation in state-level dependent coverage policies, taking advantage of the staggered timing of the reforms, and uses panel data from the US Census from 1990-2000 and the American Community Survey (ACS) from 2001-2011. The study found wage increases among young adults with dependent coverage increased 3.5-4.6 percent. For men, dependent coverage increased education by an average of .17 years. This study found more extensive impacts on labor market out than previous literature.

Alternatively, Yörük Xu use a fuzzy regression discontinuity design to examine the impacts of the ACA Dependent Coverage Mandate on young adult labor market outcomes. The study uses data from the Medical Expenditure Panel Survey, a national sample that interviews respondents five times in two consecutive years. They find that aging out of ACA's dependent coverage mandate (turning 26) is associated with a 3.7-4.3 percent increase in the probability of being employed, and a 1.9 percent decrease in the probability of being self-employed. However, the study does not find any significant impact of the parental employer insurance coverage on weekly working hours, hourly wages, or job mobility.

2.2 Contribution

My paper will contribute to literature along multiple dimensions. Firstly, I will extend the post-policy implementation period in my data to 2018. This will increase the sample size in the simple two-period DID regression model, making the results more robust and accurate than a shorter time period. Additionally, by using a dynamic difference-in-differences model, I will estimate the differential change in labor outcomes for each year before and after the ACA. This will allow me to see how the labor-market impacts of the Dependent Care Provision have changed over time.

Furthermore, previous studies using similar models have not accounted for pre-2010 state-level dependent coverage provisions. I will include these state-level provisions in order to control for effects prior to the 2010 provision. Finally, I will extend my analysis to investigate the impact of dependent coverage policies on different income groups and education levels, in order to analyze if this policy impacts demographic groups in different ways or at different magnitudes.

A potential weakness of my research is that I will not filter my sample to only young adults whose parents are confirmed to have employee-sponsored health insurance. This would require methodology similar to (Heim, Lurie, and Simon 2018) that identifies individuals using tax data. However, the larger sample size and extended period should still be able to capture potential effects.

3 Data

3.1 Demographic, Health Insurance and Labor Data

My main data source was yearly survey data from the Annual Social and Economic Supplements (ASEC) of the Current Population Survey (CPS). The ASEC is a representative national sample over 75,000 households annually. I selected annual survey data from 2005-2018. The demographic data that I sourced included gender, race, age, marital status, citizenship status, immigration status, and state.

I selected several health insurance outcome variables in order to measure the share of the sample with different health insurance types. The health insurance indicators that I selected were health insurance coverage, private health insurance coverage, Medicaid coverage, dependent health insurance coverage, employer-sponsored health insurance coverage.

I selected several dummy labor market indicators from the ASEC data. These dummies include employment status, unemployment status, self-employment status, and labor force participation status. I also selected indicators for annual income, hours worked per week, and weeks worked per year. Hours worked per week and weeks worked per year serve as proxies for part-time employment. The labor market data refers to the year prior to the sample. Table 2 displays the sample mean, treatment mean, control mean and t-statistic for each control and outcome variable.

3.2 Unemployment Data

I also used data from Federal Reserve Economic Data (FRED) for yearly unemployment rates. I include a control for yearly unemployment rates as a method to control

Table 2: Descriptive Statistics: Control and Treatment T-test

	(1) Full sample	(2) Age 22-25	(3) Age 26-29	(4) Difference (3)-(2)	
	mean	mean	mean	b	t
Age	25.57	23.52	27.52	4.00	926.82
Female	0.52	0.52	0.53	0.01	5.78
Foreign Born	0.16	0.15	0.18	0.03	23.22
Citizen	0.87	0.89	0.86	-0.02	-17.47
Married	0.33	0.22	0.44	0.23	129.51
HI Coverage	0.75	0.73	0.76	0.02	12.94
Private HI	0.62	0.60	0.63	0.03	13.53
Dependent HI	0.19	0.21	0.17	-0.05	-30.78
Employer HI	0.51	0.46	0.56	0.10	51.24
Hours/Week	37.79	36.28	39.11	2.83	50.26
Weeks/Year	45.48	43.96	46.85	2.89	52.64
Income	23318	18092	28270	10177	82.05
Hourly Wage	16.68	14.82	18.34	3.52	16.85
Employed	0.72	0.69	0.75	0.06	34.56
Unemployed	0.07	0.07	0.06	-0.01	-15.17
Self Employed	0.03	0.02	0.04	0.01	20.52
NILF	0.21	0.23	0.19	-0.05	-28.61
N	270097	131398	138699	270097	

for labor market volatility. Table 3 displays the yearly unemployment rates.

Table 3: Yearly Unemployment Rates

2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
5.2	4.7	4.4	5.1	8.7	9.9	9.0	8.2	7.5	6.7	5.4	5.0	4.4	4.0

3.3 State-level Provision Data

I manually entered data on state-level provisions from the National Conference of State Legislatures and (Depew 2015). The data in Table 1 is sourced from the Depew 2015 paper. Using this information, I created a new state-level treatment dummy variable that defines the treatment group at the state level. The state-level treatment variable is based on the eligibility qualifications in the state. These include marital status, student status, and whether the individual has children. I also created a state-level pre-post variable based on when the state level provision was implemented. We must keep in mind that beginning in 2011, all individuals in every state were in the treatment group due to the national mandate.

Table 4: State Dependent Coverage Policy Years and Eligibility Criteria

State	Full year	Eligibility Criteria			
	Implemented	Maximum age	Student	Not married	No Children
Colorado	2006	24		Yes	
Connecticut	2009	25		Yes	
Delaware	2008	23		Yes	
Florida	2008	24	Yes	Yes	Yes
Idaho	2008	24	Yes	Yes	
Illinois	2010	25		Yes	
Indiana	2008	23		Yes	
Iowa	2009	No limit	Yes	Yes	
Kentucky	2008	25		Yes	
Louisiana	2009	23	Yes	Yes	
Maine	2007	24		Yes	Yes
Maryland	2008	24		Yes	
Massachusetts	2007	25	Yes	Yes	
Minnesota	2008	24		Yes	
Missouri	2008	24		Yes	
Montana	2008	24		Yes	
New Hampshire	2007	25		Yes	
New Jersey	2006	29		Yes	Yes
New Mexico	2003	24		Yes	
New York	2010	29		Yes	
North Dokota	1995	25	Yes	Yes	
Pennsylvania	2010	29		Yes	
Rhode Island	2007	24	Yes	Yes	
South Dokota	2005	23	Yes	Yes	
Texas	2005	No limit	Yes	Yes	
Utah	1995	25		Yes	
Virginia	2007	24		Yes	
Washington	2009	24		Yes	
West Virginia	2007	24		Yes	
Wisconsin	2007	26		Yes	

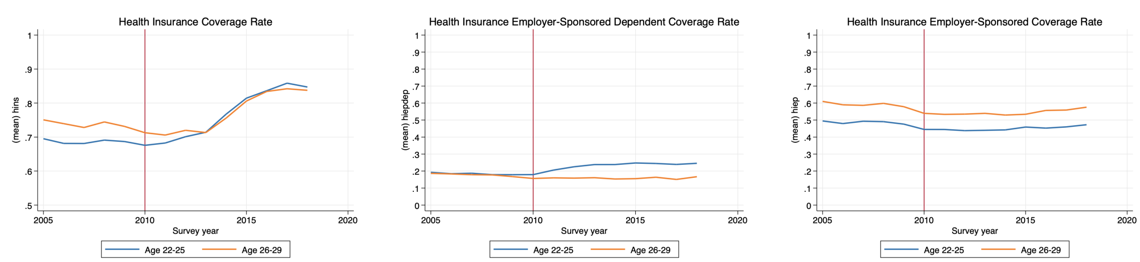
Note: This table is modeled off of a table in (Depew 2015). In 2010, all states were mandated to extend dependent coverage for all individuals under 26-years-old. The first full year implemented was 2011.

4 Model and Empirical Strategy

4.1 Methodology

I used a difference-in-differences (DID) regression model to estimate the federal mandate's impact on health insurance coverage rates and labor market outcomes. I used four different difference-in-differences models to estimate the impacts. Model 1 and Model 2 are pre-post period difference-in-differences models. Model 3 is a dynamic difference in differences model. Model 4 is a dynamic event study model. For the main regression model, the treatment group will be individuals ages 22-25 and the control group will be individuals ages 26-29. I checked for parallel trends of the controls and the dependent variables. Figure 1 displays the parallel trends for the health insurance dependent variables, labor outcome dependent variables, and controls.

While most of the variables appear to have strong parallel trends, some fail the parallel trends assumption. The NILF indicator and the employment indicator to have the most differing trends in the pre-period. For NILF, the treatment group has a steep increase prior to the intervention. For employment, the treatment group appears to decline at a greater rate than the control group. This failure of the parallel trends assumptions make the results for these dependent variables unreliable. Interestingly, for dependent coverage, the treatment and control group appear to diverge in 2009. This is due to the state-level provisions that were implemented prior to 2010. This suggests that Model 2 is likely a better estimator for this variable.



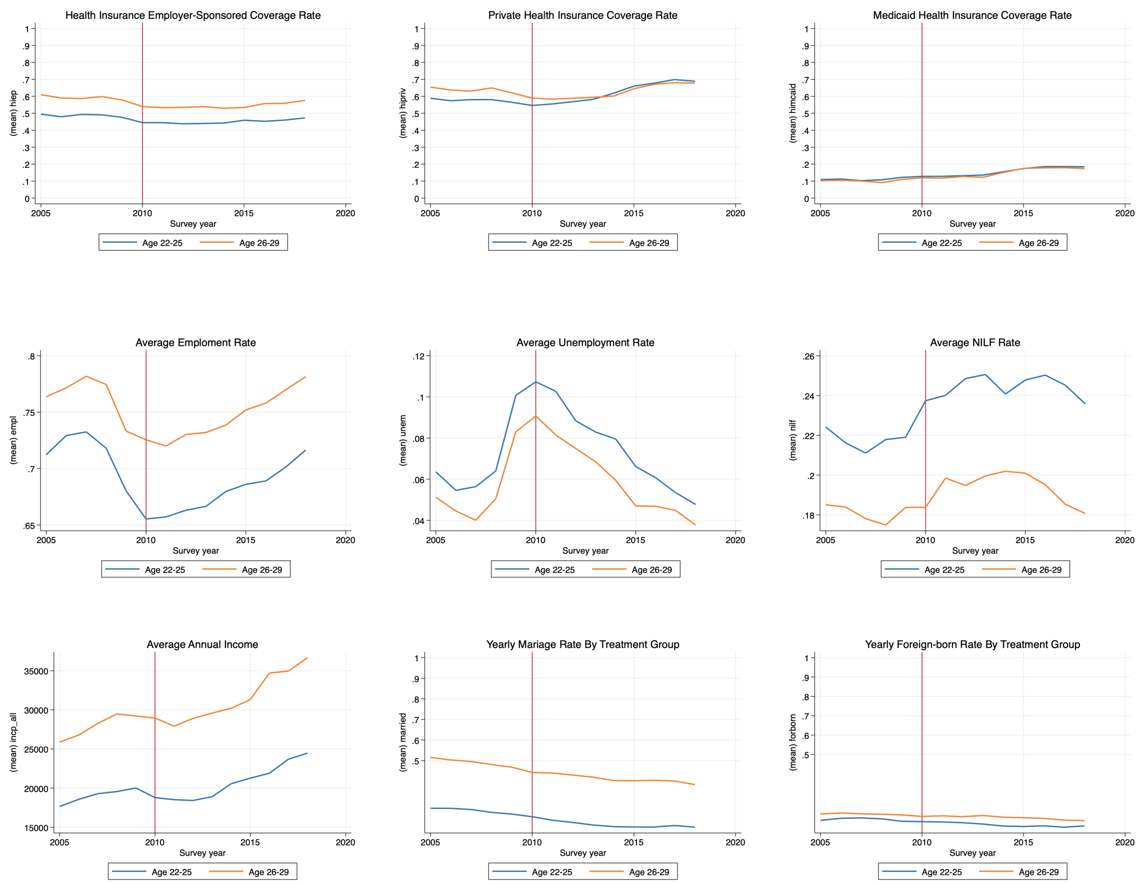


Figure 1: Parallel Trends of Dependent Variables and Controls

4.2 Models

4.2.1 Model 1

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 Ya_{it} + \beta_2 Post2010_{it} + \beta_3 (Ya_{it} \times Post2010_{it}) \\ + \beta_4 Uemp + \beta_5 M + YearFE + StateFE + \epsilon_{it} \quad (1) \end{aligned}$$

Model 1 is a simple pre-post difference-in-differences model with 2010 as the intervention year for the entire sample. The control group is individuals ages 26-29 and the treatment group is individuals ages 22-25 represented by YA in this equation. The pre-period is before 2010 and the post period is after 2010. There are also year and state fixed effects, as well as controls for unemployment and treatment. Y_i represents the various health insurance and labor outcome variables. I cluster standard errors at the state level.

4.2.2 Model 2

$$Y_{it} = \beta_0 + \beta_1 Treatment_{it} + \beta_2 Post_{it} + \beta_3 (Treatment_{it} \times Post_{it}) \\ + \beta_4 Uemp + \beta_5 M + YearFE + StateFE + \epsilon_{it} \quad (2)$$

Model 2 is also a pre-post difference-in-differences model but the treatment group and intervention year vary by state in order to control for state-level policies prior to the ACA Dependent Care Provision in 2010. $Treatment$ represents the group eligible for dependent coverage (age, marriage-status, student-status) but this varies by state. $Post$ represents the time after a state dependent coverage policy, and after the ACA Dependent Care Provision for states that did not implement a state level policy before. The controls include $Unemp$ which represents the yearly unemployment rate and M which represents the individual's marital status. Model 3 also includes state and year fixed effects. I cluster standard errors at the state level, and

4.2.3 Model 3

$$Y_{it} = \alpha + \delta Ya_{it} + \sum_{n=-5}^{8} \gamma_n Year_{it} + \sum_{m=-5}^{8} \beta_m (Ya_{it} \times Year_{it}) + \sum_{n=-5}^{8} \delta_n Controls_{it} + \epsilon_{it} \quad (3)$$

Model 3 is a dynamic difference-in-differences model that estimates the trends in the intervention effect in the post intervention years. It has the same specification as Model 1, but finds the estimator for each year after the intervention. I cluster standard errors at the state level.

4.2.4 Model 4

$$Y_{it} = \alpha + \delta Ya_{it} + \sum_{n=-5}^{10} \gamma_n Year_{it} + \sum_{m=-5}^{10} \beta_m (Treatment_{it} \times Year_{it}) \\ + \sum_{n=-5}^{10} \delta_n Controls_{it} + \epsilon_{it} \quad (4)$$

Model 4 is an event study model that estimates the trends in the intervention effect in the post intervention years. Similar to Model 3, the dynamic difference-in-differences, it finds the estimator for each year after the intervention. It has the same treatment specification as Model 2, treating the state-level policies as the event, using the intervention year and treatment requirements for each state. I cluster standard errors at the state level. In this model, we must not that each year has different sample sizes, based on when each state implemented their policy. This may contribute to differing standard errors and significance for each year.

5 Results

5.1 Health Insurance Coverage Results

Table 5: Dependent Care Provision on Health Insurance Coverage

	(1) H-Ins	(2) H-Ins	(3) H-Ins	(4) H-Ins
Post-treatment	0.040***	0.102***	0.045***	0.111***
	(0.007)	(0.012)	(0.007)	(0.013)
Age 22-25	-0.049***	-0.050***	-0.029***	-0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
Post-treatment × Age 22-25	0.050***	0.051***	0.050***	0.051***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	270097	270097	267035	267035
F-test	166.28	.	354.35	.
Controls	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
State FE	No	Yes	No	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 displays the regression estimates for the impact health insurance coverage rate variables for Model 1. I use several specifications as a test to determine the most suitable model to use for the rest of the study. I ultimately decide to include controls

Table 6: Model 1: Dependent Care Provision on Health Insurance Coverage Types

	(1) HI	(2) HI Dep	(3) HI Indep	(4) HI Priv	(5) HI Medicaid
Post-period	0.111***	0.005	-0.012	0.050***	0.078***
	(0.013)	(0.004)	(0.009)	(0.009)	(0.012)
Age 22-25	-0.028***	0.045***	-0.074***	-0.036***	0.008**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Post × Age 22-25	0.051***	0.067***	0.009*	0.059***	-0.002
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
Observations	267035	267035	267035	267035	267035
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Model 2: State Dependent Coverage Provisions on Health Insurance

	(1) HI	(2) HI Dep	(3) HI Indep	(4) HI Priv	(5) HI Medicaid
Post-period	-0.016*	-0.029***	-0.014	-0.031***	0.016*
	(0.009)	(0.006)	(0.011)	(0.008)	(0.009)
Treatment	-0.030***	0.031***	-0.080***	-0.041***	0.010***
	(0.004)	(0.006)	(0.005)	(0.005)	(0.003)
Post × Treatment	0.043***	0.062***	0.014**	0.052***	-0.006
	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)
Observations	267035	267035	267035	267035	267035
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for unemployment and marriage, as well as year and state fixed effects for the rest of the regressions.

Table 6 displays the regression results for the health insurance outcome variables for Model 1. The estimator of interest is $Post - treatment \times Age22 - 25$, the intervention effect. Table 7 displays the regression results the health insurance outcome variables for Model 2 that includes controls for state-level mandates prior to 2010. Table 6 and Table 7 indicate that the Dependent Care Provision increases health insurance coverage for the treatment group by between 4.3 and 5.1 percent. This is statistically significant at the 1 percent level. Furthermore, the estimates suggest that the policy causes the percentage of young adults in the treatment group with dependent coverage from their parents to increase by between 6.2 and 6.7 percent. This is statistically significant at the 1 percent level. The models estimate that the intervention effect on medicaid is between -.06 and -.02, and is not statistically significant. This validates that medicaid expansion in the post-period impacts the control and treatment groups similarly, not affecting the estimates. These findings align with my hypothesis.

5.2 Labor Market Outcome Results

Table 8: Model 1: Dependent Care Provision on Labor Market Outcomes

	(1) Weeks	(2) Hours	(3) Emp	(4) Unemp	(5) NILF	(6) Self-emp
Post-period	1.096***	-0.225	0.019***	-0.019***	-0.000	-0.007**
	(0.157)	(0.185)	(0.006)	(0.002)	(0.005)	(0.003)
Age 22-25	-2.403***	-2.254***	-0.060***	0.007***	0.052***	-0.013***
	(0.117)	(0.105)	(0.004)	(0.002)	(0.003)	(0.001)
Post × Age 22-25	-0.474***	-0.596***	-0.010**	0.001	0.009**	0.001
	(0.117)	(0.134)	(0.004)	(0.002)	(0.004)	(0.002)
Observations	215291	187461	267035	267035	267035	215291
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 displays the regression results for the health insurance outcome variables for Model 1. The estimator of interest is $PostTreatment \times Age22 - 25$, the intervention effect. Table 7 displays the regression results the health insurance outcome

Table 9: Model 2: State-level Dependent Coverage on Labor Market Outcomes

	(1) Weeks	(2) Hours	(3) Emp	(4) Unemp	(5) NILF	(6) Self-emp
Post-period	0.127	0.159	-0.003	0.003	0.000	-0.001
	(0.149)	(0.168)	(0.005)	(0.003)	(0.004)	(0.002)
Treatment	-2.346***	-2.190***	-0.056***	0.007***	0.050***	-0.013***
	(0.119)	(0.116)	(0.003)	(0.002)	(0.003)	(0.002)
Post × Treatment	-0.343**	-0.443***	-0.009**	0.001	0.007*	0.001
	(0.159)	(0.155)	(0.004)	(0.002)	(0.004)	(0.002)
Observations	215291	187461	267035	267035	267035	215291
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

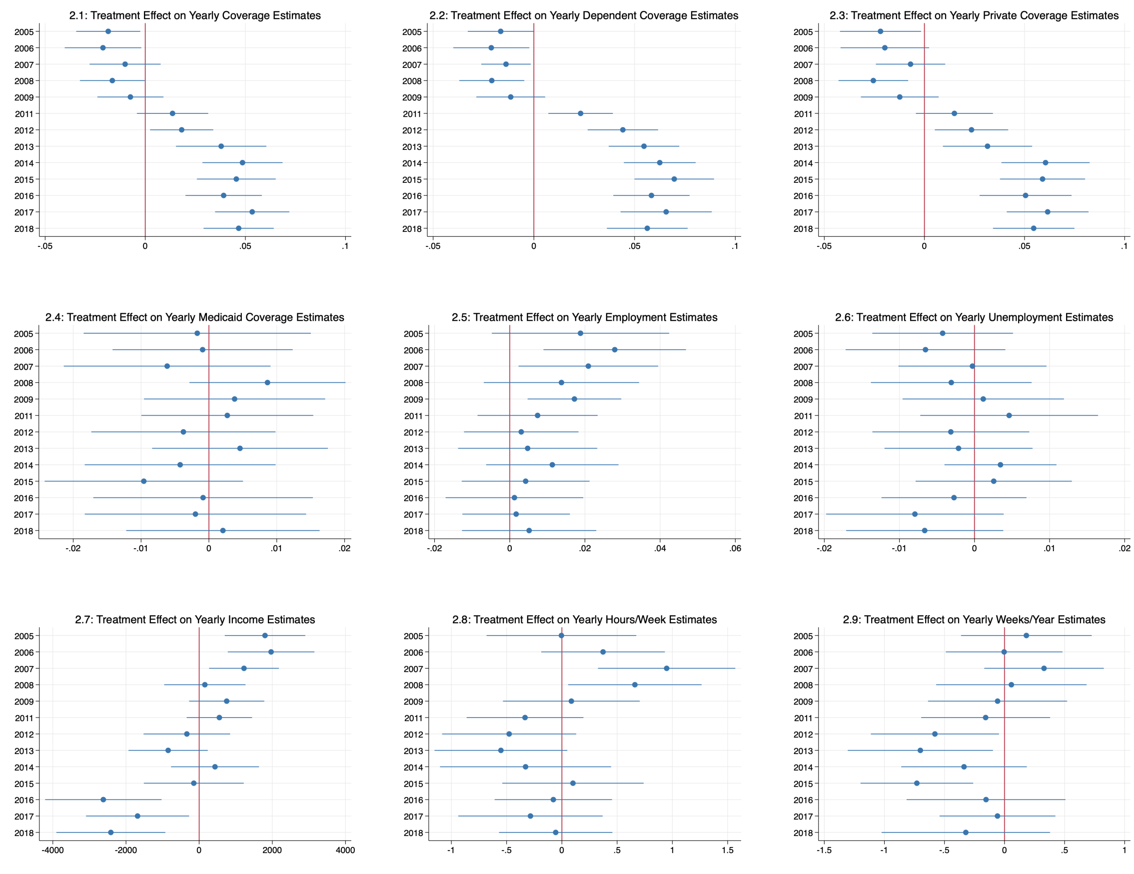
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

variables for Model 2 that includes controls for state-level mandates prior to 2010. Table 6 indicates that the Dependent Care Provision decreases the weeks worked per year by .47 , statistically significant at the 1 percent level. Table 7 indicates that dependent coverage policies decrease weeks worked per year by .34, statistically significant at the 5 percent level. Table 6 and Table 7 indicate that the dependent coverage policies decrease the hours worked per week by an average of between .443 and .596, statistically significant at the 1 percent level. These findings align with my hypothesis that the provision decreases hours and weeks worked for the treatment group. The models also find that the provision decreases employment for the treatment group by .09 and 1 percent, statistically significant at the 5 percent level. I do not find statistically significant results for the Dependent Care Provision's impact on unemployment or self-employment levels. This aligns with my hypothesis that the Dependent Care Provision will decrease employment levels of young adults.

5.3 Dynamic Difference-in-Differences Results

The dynamic difference-in-differences models display interesting trends about the lasting effects of the Dependent Care Provision. As displayed by the Graph 2.1, the effect on health insurance coverage rates increases for 5 years after the intervention until 2015. Then it levels out at around a 5 percent increase. The dependent health insurance coverage and private health insurance coverage graphs display similar increasing and then consistent trends. This is likely due to increased take up in the years after the policy. There appears to be no impact on Medicaid insurance coverage which is consistent with what I predicted.

Graph 2.5, displaying employment estimators graph shows an immediate decrease in employment in 2011 and then little effect. There also appears to be no significant or lasting effect on the self-employment and NILF indicators. The income estimator graph shows an immediate negative income intervention effect for 2011-2013, but it then levels out. The effect becomes stronger in 2016-2018 but I have doubt that this is due to the policy intervention. These model estimates is unreliable due to the nonparallel trends of the control and treatment group. The negative effect on hours and weeks worked per year appears to grow from 2011-2013 and then disappear. This can either be due to non-lasting effects or confounding factors that I am not accounting for.



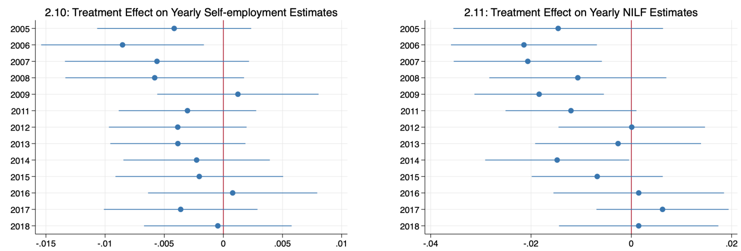


Figure 2: Model 3 Dynamic DID Coefficient Estimates

5.4 Event Study Results

The event study model estimates the long-term impacts of dependent coverage treatment status on health insurance coverage and labor market outcomes. Model 4, the event study model, treats state level policies as the event, and state-specific requirements as the treatment status. The first four graphs in Figure 3 display the estimated effect of dependent coverage qualification on health insurance coverage. Graphs 3.1, 3.2, and 3.3, displaying total health insurance coverage, dependent coverage, and private health insurance coverage, all indicate an increasing positive effect each year for seven years following treatment. Graph 3.4, displaying the estimated effect on Medicaid, does not show a clear trend.

Of the labor market outcome event study graphs, graphs 3.7 and 3.8 display the most interesting and significant results. Graph 3.7 displays the yearly estimates for the impact on average annual income. There is a growing negative trend from approximately Year 4 through Year 7. This may indicate that dependent coverage leads to lagged negative impact on the average income of eligible dependents. This would mean that the policies may influence eligible dependents to work less or work lower wage jobs. I hypothesized that the treatment group would have a higher average annual income, because they may substitute higher wage jobs for jobs that provide health insurance. Graph 3.11 displays the estimated effect on hours worked per week. We see a negative estimate beginning in year 1, but there does not appear to be a trend in the magnitude of the trend. Rather, it fluctuates from year to year following the event. We must keep in mind that these labor choice results may be influenced by external labor market factors that were not controlled for in our model. Furthermore, the event study does not indicate many long-term trends in the impact of dependent care policies on labor market outcomes.

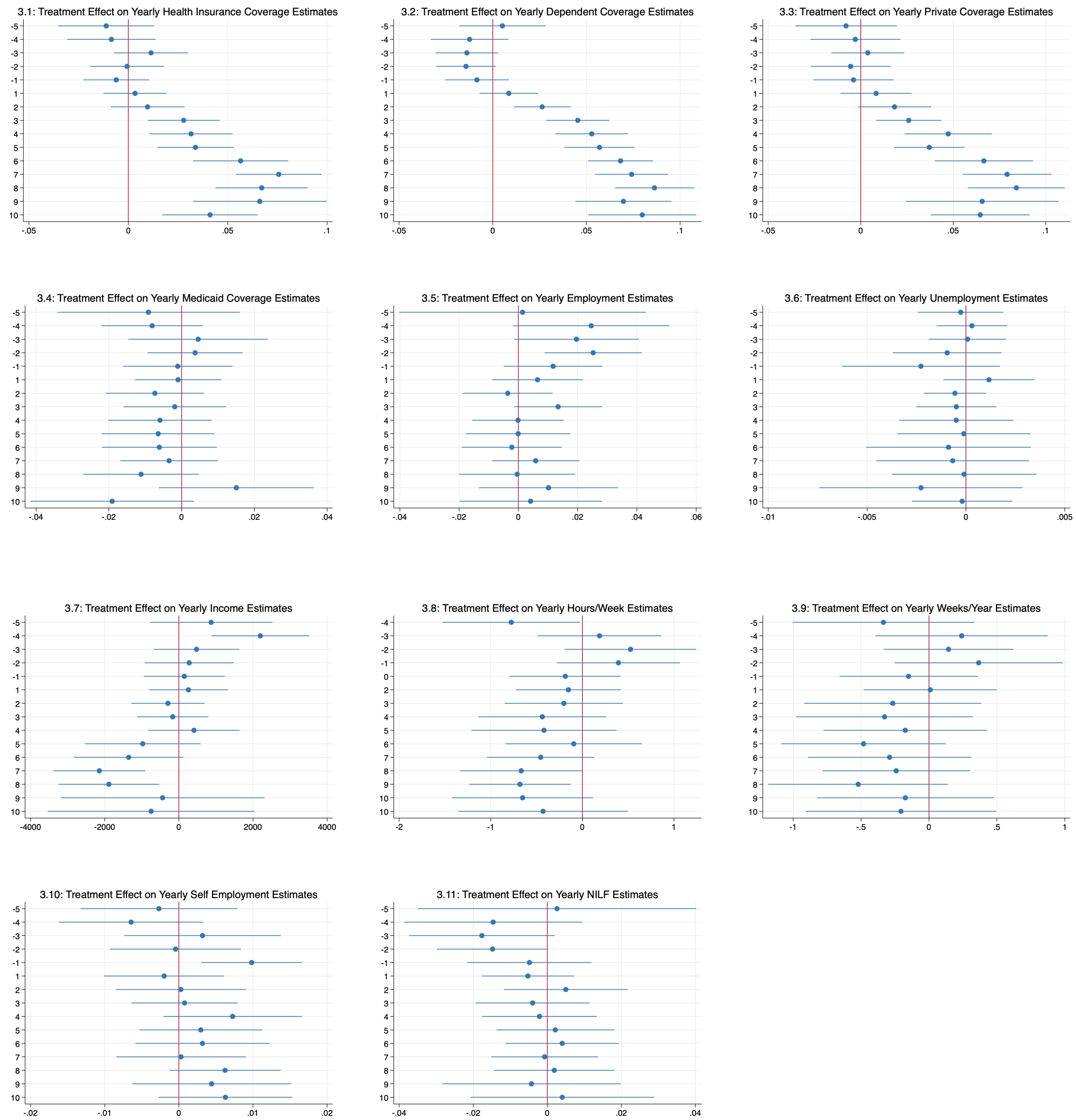


Figure 3: Model 4 Event Study Coefficient Estimates

5.5 Education and Income Groups Results

In this section, I break down the results from Model 2 by income group and educational attainment level in order to see if dependent coverage policies impact some demographics more significantly than others. In this section, I looked specifically at total health insurance coverage, hours worked per week, weeks worked per year, employment status, and self-employment status. I did find statistically significant differences between demographic groups for multiple outcome variables. While included some of these tables in this section, I have included others in the appendix.

In order to see how dependent coverage policies impact the treatment group at different education levels, I partitioned the data set by educational attainment. There are five different education levels in the data set— individuals who completed less than high school (LTHS), high school (HS), some college, college, and advanced degrees. We must note that these different subgroups vary greatly in their number of observations. While the some college group has 91,007 observations, less than high school only has 7906. This may impact the statistical significance of the results.

While I expected to find varying effects for different education levels, I found the regression results to be relatively consistent across groups. I anticipated that because educational attainment is correlated with jobs with differing health insurance coverage, there would be variance across the groups.

I found the most interesting result for the dependent variable of hours worked per week as displayed in Table 10. We can see that the estimated impact of dependent coverage on hours worked per week for dependents with less than high school education is -1.059. This is statistically significant at the 10% level and much greater than the other education groups. However, I hypothesize that this is may be because while individuals under 26 who have not completed high school are still in high school, individuals over 25 years old are in the labor force. Therefore, I do not believe that this is an impact of the dependent coverage policies.

Table 10: State-level Dependent Coverage on Hours/Week by Education

	(1) LTHS	(2) HS	(3) Some Col.	(4) College	(5) Advanced
Post-period	0.829	0.206	0.039	-0.209	-0.576
	(0.941)	(0.190)	(0.239)	(0.306)	(0.462)
Treatment	-0.144	-1.024***	-3.429***	-1.652***	-3.342***
	(0.365)	(0.154)	(0.238)	(0.192)	(0.741)
Post × Treatment	-1.059*	-0.304*	-0.411*	-0.318	-0.328
	(0.607)	(0.177)	(0.239)	(0.239)	(0.664)
Observations	4663	54822	62757	45513	11247
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In order to see how the dependent coverage policies impact the treatment group at different income levels, I partitioned the data by income quartile. I made the assumption that different income groups would have different types of insurance coverage eligibility from Medicaid to employee-sponsored health insurance. Furthermore, I predicted that they would have different elasticities of demand for health insurance. Thus, I anticipated that dependent coverage policies would affect them differently.

I found the most interesting results for hours worked per week, weeks worked per year, and employment dependent variables. Table 11 displays the results for weeks worked per year, indicating that the largest results for the first quartile and third quartile. The third quartile was statistically at the 1% level, with a reduction of .426 weeks worked per year for the treatment group. The results were very similar for hours worked per week. I hypothesize that the lowest income group experienced the largest effect on the amount worked, because they are more likely to have part-time jobs. Table 12 displays the estimated effect on employment by income level, showing a negative effect for each quartile. All of the results were statistically significant, and the magnitude decreased as the quartile rose.

Table 11: State-level Dependent Coverage on Weeks/Year by Income

	(1) 0 %	(2) 25 %	(3) 50 %	(4) 75 %
Post-period	0.925	0.063	0.200**	0.035
	(0.851)	(0.255)	(0.096)	(0.081)
Treatment	0.972	-8.710***	-1.524***	-0.689***
	(0.671)	(0.303)	(0.093)	(0.089)
Post × Treatment	-1.423	-0.327	-0.426***	-0.065
	(0.876)	(0.282)	(0.121)	(0.105)
Observations	12721	67596	71121	63853
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: State-level Dependent Coverage on Employment by Income

	(1) 0 %	(2) 25 %	(3) 50 %	(4) 75 %
Post-period	-0.014	-0.004	-0.002	-0.001
	(0.009)	(0.008)	(0.004)	(0.005)
Treatment	-0.082***	-0.108***	-0.036***	-0.019***
	(0.007)	(0.008)	(0.004)	(0.004)
Post × Treatment	-0.082***	-0.108***	-0.036***	-0.019***
	(0.007)	(0.008)	(0.004)	(0.004)
Observations	67195	67387	70050	62403
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Robustness Checks

6.1 Pre-period Placebo Intervention Test

I perform pre-period placebo intervention tests to identify if the treatment effects are actually unique to the policy intervention in 2010. I use this robustness check for the simple pre-post difference-in-differences used in Model 1. I change the intervention year from 2010 to 2007, 2008, and 2009. I reduce my sample to only include data from the years 2005-2010. I perform this test on dependent coverage rate, weeks worked per year and hours worked per week because these were my most significant results. I display the results in Table 13.

For the most part, I find insignificant results for the pre-period intervention tests. For Post-2007, there were no statistically significant results. For Post-2008, the increase in dependent coverage was statistically significant at the 10 percent level. The decrease in hours worked per week was significant at the 5 percent level.For Post-2009, the increase in dependent coverage was statistically significant at the 5 percent level. This is likely due to the state-level provisions enacted before 2010. The reduction hours worked per week was statistically significant at the 10 percent level. The significant results for hours worked per week suggest that there may have been unobserved forces that made the groups diverge in the per-period. This threatens the parallel trends assumption used in our model.

Table 13: Pre-Period Placebo Intervention Test

	Post 2007			Post 2008			Post 2009		
	(1) Hi-Dep	(2) Weeks	(3) Hours	(4) Hi-Dep	(5) Weeks	(6) Hours	(7) Hi-Dep	(8) Weeks	(9) Hours
Post	-0.012***	-0.880***	-1.240***	-0.015***	-0.878***	-1.119***	-0.016***	-0.906***	-1.137***
	(0.004)	(0.159)	(0.186)	(0.004)	(0.148)	(0.193)	-0.016***	-0.906***	-1.137***
Age 22-25	0.049***	-2.307***	-2.172***	0.048***	-2.336***	-2.124***	0.049***	-2.378***	-2.206***
	(0.005)	(0.108)	(0.120)	(0.004)	(0.124)	(0.114)	(0.004)	(0.130)	(0.110)
Post × Age 22-25	0.004	-0.189	-0.214	0.010*	-0.195	-0.475**	0.013**	-0.137	-0.441*
	(0.004)	(0.147)	(0.177)	(0.005)	(0.149)	(0.226)	(0.007)	(0.212)	(0.244)
Observations	120335	98300	84473	120335	98300	84473	120335	98300	84473
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2 Different Comparison Groups

A potential problem with my model is that the control and treatment group have unobserved differences due to the large age bins. A 22 year old's labor market choices are quite different from a 29 year old's due to different priorities and experience. One could argue that the control and treatment groups are not similar enough to be compared. In order to test if the results are valid, I altered the age bins and re-ran the regressions. I ran the Model 2 regressions with 1 year bins, 2 year bins, and 3 year bins for the control and treatment groups. The original model uses Age 22-25 for the treatment group and Age 26-29 for the control group. Alternatively, Table 14 shows the results using a sample of Age 25-26, Table 15 shows the results using a sample of Age 24-27, and Table 16 shows the results using a sample of Age 23-28. Overall, this robustness check suggests consistent yet less significant results as the age buckets shrink.

Table 14: State-level Dependent Coverage on Labor Market Outcomes Age 25-26

	(1) Weeks	(2) Hours	(3) Emp	(4) Unemp	(5) NILF	(6) Self-emp	(7) Income
Post-period	-0.277	0.220	-0.010	0.007	0.003	-0.001	183.009
	(0.197)	(0.269)	(0.007)	(0.005)	(0.007)	(0.003)	(824.049)
Age 25	-0.016	-0.437**	-0.006	-0.001	0.007	-0.001	-1540.576***
	(0.172)	(0.201)	(0.007)	(0.004)	(0.005)	(0.003)	(285.926)
Interaction	-0.363*	-0.039	-0.008	0.002	0.006	-0.000	-132.078
	(0.207)	(0.244)	(0.008)	(0.004)	(0.007)	(0.004)	(371.089)
Observations	54760	47870	67173	67173	67173	54760	67988
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows consistent yet less significant results using the 1 year age buckets. Young adults age 25 and age 26 are the most demographically similar groups, but this model also has a much smaller sample size than the original model. Although the model estimates a similar effect, the results are not as statistically significant. We still see a decrease in weeks worked per year and hours worked per week, and little impact on the employment outcomes. Table 15 displays the results using 2 year age buckets. Again, the results show a consistent pattern. Table 16 displays the results using 3 year age buckets. As expected these results most closely resemble those of the original model. Overall, as the age buckets expand, the results become more significant. Note that this may be due to unobserved differences between the older and younger samples or due to the larger sample size.

Table 15: State-level Dependent Coverage on Labor Market Outcomes Age 24-27

	(1) Weeks	(2) Hours	(3) Emp	(4) Unemp	(5) NILF	(6) Self-emp	(7) Income
Post-period	-0.116	-0.031	-0.006	0.002	0.004	-0.000	-159.671
	(0.185)	(0.214)	(0.006)	(0.003)	(0.005)	(0.003)	(675.989)
Age 24-25	-0.749***	-0.841***	-0.020***	0.001	0.019***	-0.006***	-4559.682***
	(0.137)	(0.172)	(0.004)	(0.002)	(0.003)	(0.002)	(316.200)
Interaction	-0.423**	-0.235	-0.008	0.004	0.005	-0.001	-172.285
	(0.173)	(0.170)	(0.006)	(0.003)	(0.005)	(0.003)	(303.794)
Observations	108750	95079	133371	133371	133371	108750	134956
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: State-level Dependent Coverage on Labor Market Outcomes Age 23-28

	(1) Weeks	(2) Hours	(3) Emp	(4) Unemp	(5) NILF	(6) Self-emp	(7) Income
Post-period	0.066	0.065	-0.006	0.003	0.003	-0.003	316.319
	(0.179)	(0.179)	(0.005)	(0.003)	(0.004)	(0.002)	(564.359)
Age 23-25	-1.544***	-1.433***	-0.039***	0.005**	0.034***	-0.010***	-6486.52***
	(0.120)	(0.134)	(0.003)	(0.002)	(0.003)	(0.002)	(297.661)
Interaction	-0.412**	-0.323**	-0.006	0.003	0.004	0.000	-773.91**
	(0.166)	(0.147)	(0.005)	(0.003)	(0.005)	(0.002)	(311.881)
Observations	162104	141675	199782	199782	199782	162104	202106
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

This study examined the impact of the dependent health insurance eligibility on labor market choices for young adults. I looked specifically at the 2010 Affordable Care Act as well as prior state-level dependent coverage provisions. Not only did

I find a statistically significant increase in health insurance coverage of 5.1%, but I also found statistically significant estimates of the impact on weeks worked per year and hours worked per week. The intervention effect was a decrease of .47 weeks worked per year and .6 hours worked per week. I found no statistically significant impact on self-employment rates, and a decrease in employment of .09% significant at the 5 percent level. I did not find reliable outcomes for income and NILF due to nonparallel trends.

As found by other researchers, there are connections between an individual's health insurance coverage status and their labor market choices. This study looked specifically at young adults, and how policy changes can impact these choices. There are several ways in which this research can be improved upon and extended. One could use panel data with repeated individuals to look directly at an individual's labor market choices based on dependent coverage. Furthermore, one could research young adults' elasticity of demand for health insurance and how this correlates with their labor market choices.

8 Appendix

Table 17: State-level Dependent Coverage on Weeks/Year by Education

	(1) LTHS	(2) HS	(3) Some Col.	(4) College	(5) Advanced
Post-period	0.850	-0.155	0.168	0.237	-0.576
	(0.767)	(0.236)	(0.274)	(0.253)	(0.462)
Treatment	-1.472***	-1.474***	-2.354***	-3.627***	-3.342***
	(0.531)	(0.158)	(0.210)	(0.212)	(0.741)
Post × Treatment	-0.523	-0.189	-0.258	-0.355	-0.328
	(0.718)	(0.189)	(0.258)	(0.250)	(0.664)
Observations	5215	64176	73600	49707	11247
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: State-level Dependent Coverage on Health Insurance by Education

	(1) LTHS	(2) HS	(3) Some Col.	(4) College	(5) Advanced
Post-period	-0.009	-0.017	-0.014*	-0.014	0.003
	(0.030)	(0.011)	(0.007)	(0.009)	(0.012)
Treatment	-0.024	-0.031***	-0.004	-0.012*	-0.029*
	(0.016)	(0.006)	(0.006)	(0.006)	(0.015)
Post × Treatment	0.038*	0.048***	0.043***	0.030***	0.025
	(0.019)	(0.007)	(0.008)	(0.008)	(0.016)
Observations	7906	83143	91007	57383	13010
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: State-level Dependent Coverage on Self Employment by Education

	(1) LTHS	(2) HS	(3) Some Col.	(4) College	(5) Advanced
Post-period	-0.014	0.005	-0.003	-0.006	-0.009*
	(0.013)	(0.004)	(0.003)	(0.003)	(0.005)
Treatment	-0.016*	-0.015***	-0.015***	-0.013***	-0.004
	(0.009)	(0.003)	(0.003)	(0.003)	(0.004)
Post× Treatment	0.002	0.002	0.000	0.003	0.008
	(0.014)	(0.004)	(0.003)	(0.003)	(0.009)
Observations	5215	64176	73600	49707	11247
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: State-level Dependent Coverage on Employment by Education

	(1) LTHS	(2) HS	(3) Some Col.	(4) College	(5) Advanced
Post-period	-0.032	-0.004	-0.005	0.004	-0.019
	(0.023)	(0.008)	(0.008)	(0.008)	(0.014)
Treatment	-0.040	-0.041***	-0.059***	-0.046***	-0.079***
	(0.024)	(0.006)	(0.006)	(0.007)	(0.014)
Post × Treatment	0.004	0.001	-0.012*	-0.005	-0.014
	(0.024)	(0.007)	(0.006)	(0.007)	(0.015)
Observations	7905	82057	89501	56973	12956
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: State-level Dependent Coverage on Hours/Week by Income

	(1) 0 %	(2) 25 %	(3) 50 %	(4) 75 %
Post-period	0.637	0.114	0.251	-0.156
	(0.725)	(0.188)	(0.225)	(0.263)
Treatment	-0.057	-4.777***	-2.815***	-1.825***
	(0.598)	(0.192)	(0.145)	(0.211)
Post × Treatment	-1.078	-0.259	-0.477**	0.121
	(0.782)	(0.234)	(0.193)	(0.251)
Observations	14607	51375	63230	58249
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: State-level Dependent Coverage on Self Employment by Income

	(1) 0 %	(2) 25 %	(3) 50 %	(4) 75 %
Post-period	0.011	-0.001	-0.001	0.001
	(0.028)	(0.001)	(0.001)	(0.001)
Treatment	0.203***	0.000	0.000	-0.000
	(0.017)	(0.001)	(0.000)	(0.000)
Post × Treatment	-0.026	0.000	0.000	-0.000
	(0.026)	(0.001)	(0.000)	(0.000)
Observations	12721	67596	71121	63853
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: State-level Dependent Coverage on Health Insurance by Income

	(1) 0 %	(2) 25 %	(3) 50 %	(4) 75 %
Post-period	-0.004	-0.023*	-0.027***	-0.016**
	(0.017)	(0.012)	(0.009)	(0.008)
Treatment	0.017*	0.031***	-0.130***	-0.074***
	(0.009)	(0.008)	(0.008)	(0.007)
Post × Treatment	0.042***	0.054***	0.063***	0.032***
	(0.009)	(0.009)	(0.009)	(0.008)
Observations	67527	67596	71121	63853
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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