

Expanded dependent health insurance coverage and the labor supply of young adults: Outcomes from state policies and the Affordable Care Act

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This Draft: January 16, 2013

Abstract

One of the first pieces of legislation to be implemented under the Affordable Care Act (ACA) was the expansion of dependent health insurance coverage for young adults. However, little is known about the potential labor market outcomes that may arise from the policy. In this paper I use changes in state policies and the ACA to examine the effect of dependent health insurance coverage on the labor market, higher education, and marital decisions of young adults. Prior to the ACA, there was no uniform policy on dependent coverage in the United States. In the early 2000s, states began implementing policies to expand dependent coverage of young adults. Using variation in the timing of policy implementation across states and eligibility criteria within states, I find that these policies decreased the labor supply of eligible young adults. In addition, I find evidence that females were more likely to be full-time students as result of the dependent coverage laws. I extend the analysis to the Affordable Care Act which expands the ability of individuals to obtain health insurance through their parent's plan until the age of 26. I find that the ACA caused an increase in the health insurance rate and a decrease in the labor supply of young adults. This decrease in labor supply is accompanied with an increase in young adults being full-time students. In addition to providing information about the consequences of expanding dependent health insurance coverage, this paper makes a novel contribution by showing that health insurance is an important determinant in the labor market decisions of young adults.

Feedback received at The University of Arizona is greatly appreciated. Price Fishback, Theresa Gutberlet, Gautam Gowrisankaran, Kei Hirano, Taylor Jaworski, Ashley Langer, Mindy Marks, Ron Oaxaca, Jessamyn Schaller, Todd Sorensen, and Tiemen Woutersen provided helpful feedback.

1 Introduction

The Affordable Care Act (ACA) drastically reshaped the health insurance landscape for young adults by allowing individuals under the age of 26 to remain on their parent's employer based health insurance plan. This paper estimates the effect of expanded dependent coverage on the labor market, higher education, and marital decisions of young adults. While many provisions of the ACA have been debated, the law to expand dependent coverage has received favorable reviews from both sides of the aisle (H.R. 3970 2009, H.R. 4038 2009). Early estimates of the efficacy of the law show large increases in the health insurance coverage rate of affected young adults (Antwi, Moriya and Simon 2012). However, policies to expand health insurance to young adults through their parent's health insurance plans may have unintended consequences in the labor market. A young adult who is able to acquire health coverage through a parent's plan may have no need of their own employer-sponsored insurance. Depending on the value of health insurance to a young adult, expanding dependent coverage may cause an affected individual to change employment or entirely exit the labor force. In addition, changes in dependent coverage laws may also affect the decisions of young adults to attend college or university and get married. The young adult population of 19-29 year-olds is important to policy makers because not only are they the largest uninsured group in the U.S., their decisions in regards to human capital accumulation through on the job employment and higher education play an important role in the continuing development of the American economy.

To identify the effect of dependent coverage on the decisions of young adults, I use two approaches: First, I exploit variation in the timing and generosity of state policies prior to the ACA that expanded the eligibility criteria for young adults to gain coverage on their parent's health insurance plans. Second, I extend the analysis to the recent health care reform (ACA) that increased the federal age limit for adult children to remain on their parent's health insurance plan. Therefore, I am able to use two sources of policy variation in two separate analyses to estimate the effects of dependent health insurance coverage. This identification strategy allows me to plausibly eliminate other contemporaneous effects that may also induce change in labor market outcomes of young adults. Previous studies have focused on the impact of the state laws and the ACA on health

insurance rates (Monheit, Cantor, DeLia and Belloff 2011, Levine, McKnight and Heep 2011, Antwi et al. 2012).¹ The contribution of this paper rests in not only providing an analysis of a significant policy, but more importantly, it provides evidence that the labor market decisions of young adults are dependent on access to health insurance coverage.

Utah was the first state to implement an extended coverage law in 1995 and by 2010 over half the states had enacted similar laws. Insurance companies in states with no expanded coverage law allowed children under the age of 19 to qualify as dependents on a parent's policy. However, if a child was a full-time student and not married then she could stay on the policy until the age of 23. The state laws implemented to expand dependent coverage varied by both the age limit set by the state as well as additional criteria such as student status, marital status, and whether the dependent had her own children. In order to estimate the effect of state laws to expand dependent coverage, I exploit the variation of policy implementation across time and eligibility requirements within a state. These two margins of variation allow me to use a difference-in-difference-in-difference framework. I compare the change in outcomes of individuals who were eligible in states who have implemented a policy to expand coverage to individuals within the same state who were not eligible for the policy. In addition, I control for differences between young adults in non-policy states who have characteristics that would either classify them as eligible or ineligible.

By studying the identification environment that these state policies provide, I find no evidence of endogenous policy adoption of states. One limitation to the state-policy analysis is that individuals could potentially select into treatment. Although the age limit set by the state is exogenous to the individual, states that require individuals to be full-time students or not be married may have individuals respond to the policy by enrolling in school or delaying marriage. I estimate the role of selection for states that required young adults to be full-time students, unmarried, or without children to be covered by the parents' insurance. I find no statistical evidence that individuals were selecting into treatment.

The ACA expanded dependent coverage to all individuals under the age of 26 who had a parent

¹Monheit et al. (2011) and Levine et al. (2011) study the impact of the state expanded dependent coverage laws on health insurance rates. (Antwi et al. 2012) studies how effective the first year of the ACA has been on increasing the insurance rates of young adults.

with employer-sponsored insurance. Factors such as student or marital status do not affect the eligibility of the dependent. To estimate the preliminary effects of the ACA, I compare the labor supply, education, and marriage decisions for individuals below the age cutoff to individuals above the age cutoff before and after the policy. Current work by Antwi et al. (2012) provides strong evidence that the ACA increased the likelihood that individuals under the age of 26 are covered under a parent's plan, are less likely to have an individually purchased plan, and are less likely to have their own employer coverage. They find the net effect is an increase in the health insurance rate of 19 to 25 year-olds. However, no study has yet to analyze potential unintended labor market outcomes of the ACA.

The labor supply decisions of young adults have large policy implications. If expansions in dependent coverage are responsible for decreases in the labor supply of young adults, the reduced labor market experience will result in a decrease in the amount of on-the-job training. Individuals who exit the workforce may or may not reinvest in human capital through higher education. A decrease in human capital accumulation will decrease the productivity of the U.S. workforce and increase production costs. These negative outcomes would lead to diminished living standards for the American economy (Kaestner 1994). However, if distortions in the labor market already exist and individuals exit the labor force to reinvest in higher education, the welfare implications may be positive. Therefore, the net potential welfare implications of expanding health insurance coverage are not clear.²

When studying the impact of the state laws, my first stage results for health insurance coverage are consistent with the prior work of Monheit et al. (2011) and Levine et al. (2011). I find a strong effect of the policy on dependent health insurance coverage. The analysis of the state laws and labor market outcomes suggest that young adults significantly decreased their labor supply as a result of gaining dependent coverage. Using a falsification test, I find no evidence that the results are being driven by contemporaneous effects to the control group. When I limit the sample to observations prior to the *Great Recession*, I find similar results as those presented in the main specification.

²Kolstad and Kowalski (2012) study the 2006 Massachusetts health reform and find that mandated employer based insurance had less associated dead weight loss than providing insurance through a tax on wages. Colla, Dow and Dube (2011) study the San Francisco health insurance mandate using a spatial discontinuity design and find no change in employment and earning of workers in San Francisco.

Therefore, the results are not being driven by the treated individuals behaving differently in the recession than the non-treated individuals. Furthermore, I find that females are more likely to be full-time students as a result of the state policies.

Similar to the findings from the state laws, I find that the ACA caused treated females and males to decrease their labor supply. Furthermore, I find evidence that those affected by the law are more likely to become full-time students. In addition, I find that females are less likely to be married given that they can qualify for coverage through a parent. However, I find no effect on the marriage outcomes of males.

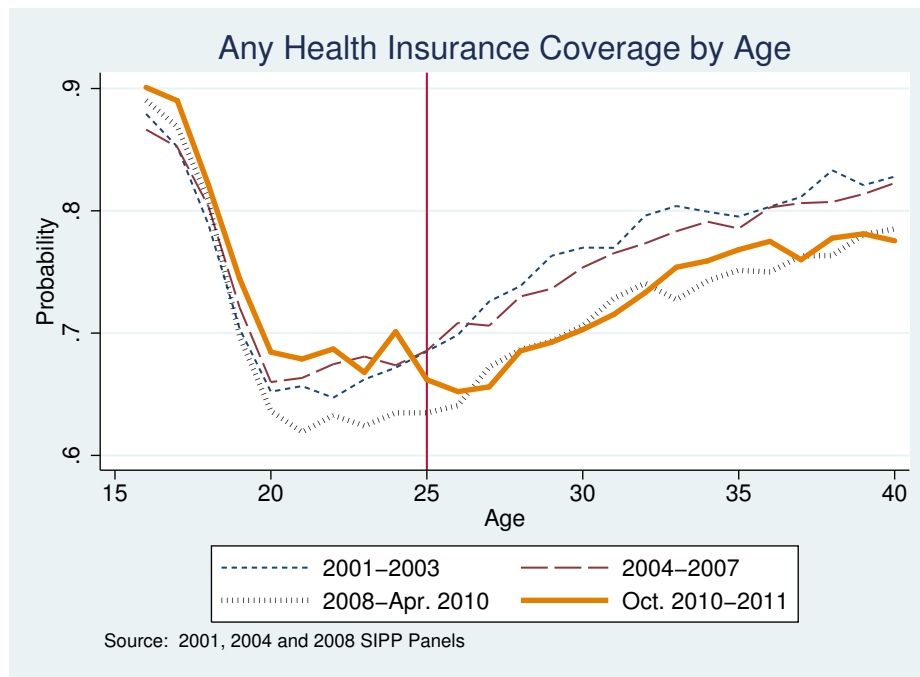
In the remainder of the paper I provide an overview of the health insurance trends of young adults in the U.S. and the role of state and federal legislation to expand coverage rates. I then discuss the general labor supply outcomes that are expected from the state and federal policies. After a section discussing the data, I lay out the identification strategy and estimate the effect of expanded dependent coverage laws on the health insurance, labor supply, and social outcomes of young adults. I then analyze internal threats to validity by testing for endogenous policy adoption and selection into treatment. I conclude the state policy section with a falsification test to rule out the possibility that contemporaneous effects in the control groups are driving the results and a robustness check that limits the data to the pre- *Great Recession* time period. I then turn to the ACA by discussing how I identify the effect of the federal policy. After an analysis on pre-treatment trends, I estimate the effect of the federal law on the same set of health insurance, labor supply, and social outcomes as previous. I conclude with a brief discussion of the broader implications of the results as well as their limitations and potential extensions.

2 Expanding Dependent Health Insurance

2.1 Uninsured Young Adults

In 2008, young adults between the ages of 19 and 29 made up 17 percent of the population but accounted for 30 percent of the 46 million uninsured individuals in the U.S. (Nicholson, Collins, Mahato, Gould, Schoen and Rustgi 2009). Figure 1 shows the health insurance coverage rate by age over four time periods. At age 18 nearly 90 percent had some form of health insurance. However, at age 19 this rate decreased by 15 to 20 percent. After age 25 these rates slowly increase to around 80 percent by age 40. Figure 1 provides insight into the effectiveness of the Affordable Care Act in increasing the health insurance rates of 19-25 year-olds. Comparing the time period January 2008-April 2010 to the time period October 2010-November 2011 shows that the insurance rate of individuals 19-25 year-olds increased by approximately 5 percent.³

Figure 1: Any Coverage by Age

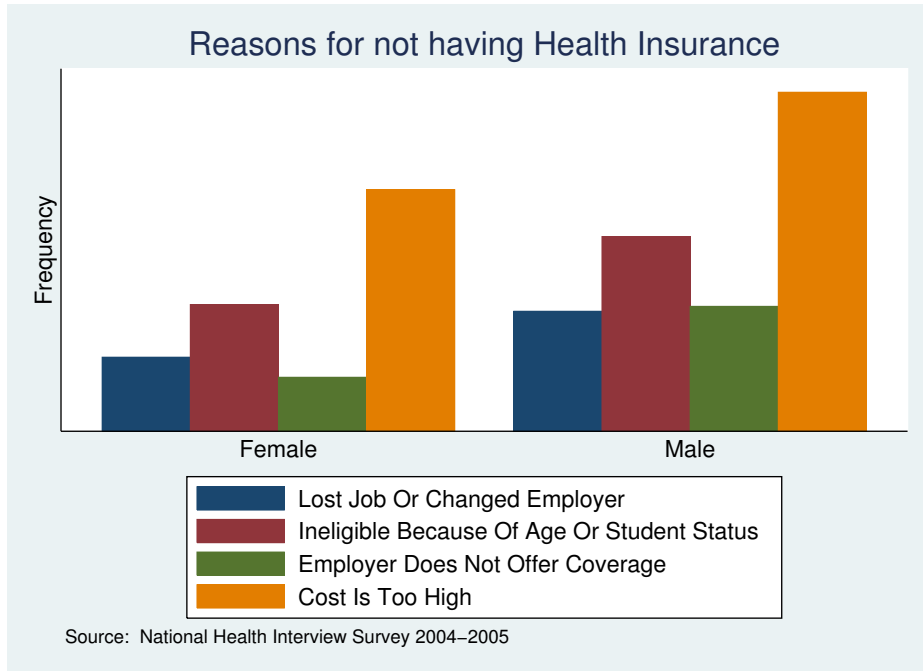


³Although the expansion of dependent coverage through the ACA was implemented on September 23rd, 2010, the Secretary of Health and Human Services asked insurance companies to begin covering young adults in May. Many insurance companies responded to this call for early adoption.

There are a number of reasons why the rate of health insurance among young adults declines dramatically at age 19. Individuals who receive health insurance through Medicaid or State Children’s Health Insurance Program (SCHIP) as dependents are excluded from these public programs once they turn 19 years of age. The sharp decline in health insurance coverage has been recently well documented in the health economics literature. Levine et al. (2011) and Anderson, Dobkin and Gross (2012) use the quasi-experimental variation in insurance status that results at age 19. Levine et al. (2011) study the impact of individuals who age out of SCHIP on health insurance outcomes. Similarly, Anderson et al. (2012) use this age cut-off to study the effects of health insurance coverage on the use of medical services.

The National Health Interview Survey specifically asks individuals without health insurance why they are not covered by an insurance policy. Figure 2 shows the frequency of the four most common reasons given for not having health insurance for individuals ages 19 to 25 (respondents were allowed to have multiple responses). Being ineligible because of age or student status was the second most common reason next to the high cost of health insurance.

Figure 2: Reasons for not having Health Insurance: Ages 19-25



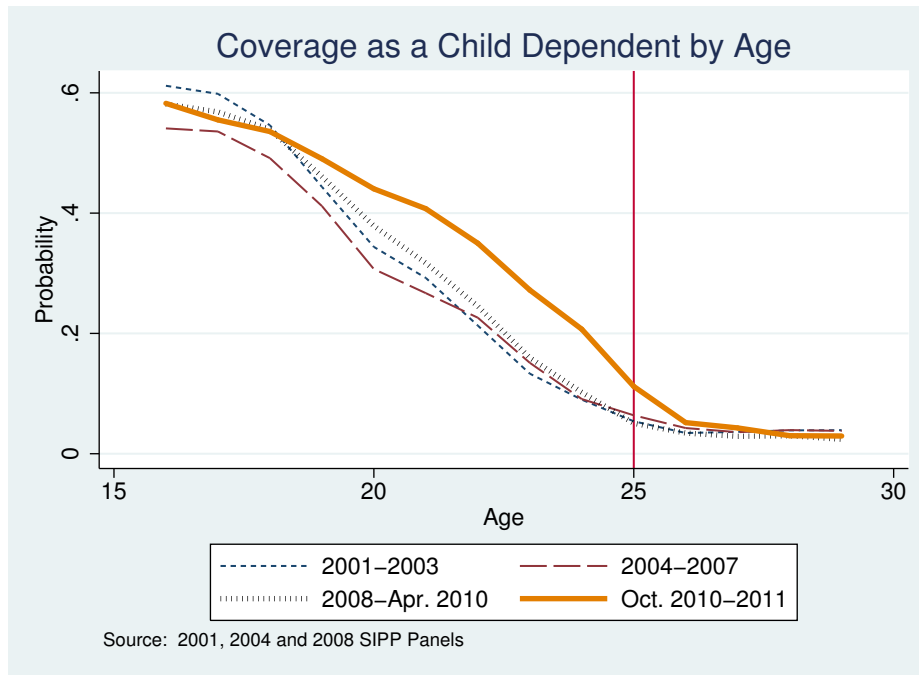
Prior to the passing of the ACA, unless a state policy had been implemented to expand dependent coverage, most employer plans did not cover dependents after the age of 18 unless they were enrolled in a college or university as a full-time student. If they were full-time students, they most often could be covered as dependents through the age of 22. As pointed out by Levine et al. (2011), employers had strong incentives from the tax code to follow these age limits. Prior to the Affordable Care Act (ACA), Internal Revenue Code Section 105 states that an employee's child must qualify as a tax dependent in order for the value of the dependent's employer-sponsored health insurance coverage to be excluded from income, and therefore tax-free, at the federal level. Dependents had to be under the age of 19, or under the age of 24 if they were a full-time student, to be considered a tax dependent and thus for their health insurance to be treated as a nontaxable benefit. In addition, Internal Revenue Code Section 106 allows the employer's premium payments for health insurance for an employee and their eligible dependents to be treated as non-taxable income to the employee (Pie 2004). Providing health insurance to dependents above these age limits would be costly to an employer.

Young adults who are full-time students without dependent coverage are often insured through college and university plans. Approximately 38 percent of public four-year universities and colleges and 79 percent of private four-year universities and colleges require students to have health insurance Nicholson et al. (2009).⁴ Individuals planning to attend institutions that require health insurance coverage face a higher cost to enroll if they do not qualify for dependent coverage.

Figure 3 shows the rate at which individuals were covered as child dependents for the same four periods as Figure 1. Prior to the passing of the ACA, the rate of dependent coverage was very similar across time. From the 2004-2007 period to the 2008-April 2010 period there is a modest increase in the rate of dependent coverage for individuals 19 to 22 years old. Whether this is due to a large number of states enacting policies to expand dependent coverage during this time or other contemporaneous effects is not clear from the simple summary statistics. However, Figure 3 does suggest that there was a large increase in the rate of dependent coverage after the ACA was implemented.

⁴California, Idaho, Illinois, Massachusetts, Montana, and New Jersey require that full-time undergraduate students who are U.S. citizens or permanent residents have health insurance (Nicholson et al. 2009).

Figure 3: Dependent Coverage by Age



2.2 State Policies to Expand Dependent Health Insurance Coverage

Prior to the passing of the ACA, no national dependent coverage law existed. However, in the late 2000s many states had either passed laws or were in the process of passing them prior to the ACA. The state of Utah was the first to enact a law to widen access to health care for young adults. It increased the cut-off age that individuals could be defined as a dependent on the parent's health insurance to 26. No other states followed suit until 2003, but by January 1st, 2010, 31 states had implemented state laws to expand dependent coverage.⁵

Table 1 presents the implementation year of state dependent coverage laws. When states enacted laws to expand dependent coverage, firms were typically required to abide by the new law upon renewal of the policy. Using tax records from firm welfare plans in 2009, I find that approximately two-thirds of plans renewed their policy in January. For this reason, in Table 1 the indicated implementation year is for the following January if the policy was implemented in any month

⁵Louisiana, North Dakota, Ohio, Oregon and Wyoming either implemented laws after January 1st, 2010 or had passed laws that were scheduled to be implemented prior to the passing of ACA.

other than January; implementation year is therefore defined “Full Year Implemented.” Table 1 also indicates the eligibility criteria that dependents must satisfy to be eligible as a dependent for health insurance. The maximum age in Table 1 represents the oldest age before becoming ineligible. It was most common for states to set the maximum age at 24 or 25 years-old. In addition to age limits, states also set eligibility criteria based on other factors. Three of the common criterion that are easily measurable are: full-time student status, marital status, and whether an individual has children. As shown in Table 1, nearly every state required eligible dependents to be single. Five states required individuals to be full-time students and four states required individuals to not have their own children. In addition, some states required individuals to be financially dependent on their parents or live at home if they were not full time students. In all, these state policies often had their largest impact by simply lifting the restriction that children had to be full-time students to qualify for dependent coverage.

The efficacy of expanding dependent coverage is mitigated because these state laws did not apply to all insurance policies of parents. First, these state laws are not applicable to public insurance. Therefore, parents on Medicare or Medicaid are not able to provide dependent coverage for their children. Second, self-insured firms (firms that assume the financial risk by paying claims directly instead of contracting with an insurance carrier) do not have to comply with state health insurance regulation. The Medical Expenditure Panel Survey shows that in 2009, 35.1 percent of private-sector firms that offered health insurance were self-insured. However, because only large firms are typically able to take on the financial risk of self-insurance, these 35.1 percent of firms enrolled 56.1 percent of private-sector enrollees who had health insurance (Agency for Healthcare Research and Quality 2009).⁶

Two previous papers have studied the impact of expanding dependent coverage laws on the insurance rates of young adults. Monheit et al. (2011) uses a difference-in-difference (DD) estimation strategy by comparing differences in the health insurance rates young adults before and after a states implement expanded dependent coverage laws. Monheit et al. (2011) find no significant evi-

⁶A report to congress (Solis 2012) shows that 16 percent of firm health plans were self-insured, 44 percent were fully-insured and 40 percent had components of both self and full insurance. Mix-insured is the result of a welfare benefit plan providing multiple types of welfare benefits (health, vision, dental, life, etc.), some of which are fully-insured and other self-insured (Brien and Panis 2011).

Table 1: State Dependent Coverage Laws

State	Full Year Implemented ^a	Eligibility Criteria			
		Maximum Age	Student	Not Married	No Children
Colorado	2006	24		Yes	
Connecticut	2009	25		Yes	
Delaware	2007	23		Yes	
Florida	2007	24		Yes	Yes
Georgia	2006	24		Yes	
Idaho ^b	2007	24	Yes	Yes	
Iowa	2010	25	Yes	Yes	
Illinois ^c	2004	26	Yes	Yes	
Indiana	2007	23			
Kentucky	2008	24		Yes	
Maine	2007	24		Yes	Yes
Maryland	2008	24		Yes	
Massachusetts	2007	25			
Minnesota	2008	24		Yes	
Missouri	2008	25		Yes	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	
Pennsylvania	2010	29		Yes	
Rhode Island	2007	24	Yes	Yes	
South Carolina	2010	24		Yes	
South Dakota	2007	29	Yes		
Tennessee	2008	24			
Texas	2005	24		Yes	
Utah	1995	25		Yes	
Virginia	2007	24	Yes		
Washington	2009	24		Yes	
West Virginia	2007	24		Yes	
Wisconsin	2010	26		Yes	

^a Full Year Implemented is the first full calendar year the policy was implemented.

^{b,c} In addition, Idaho and Illinois expanded coverage to all individuals under twenty-one years of age and and twenty-two years of age, respectively.

Sources: (Nicholson et al. 2009); (National Conference of State Legislatures 2010); (Levine et al. 2011); (Monheit et al. 2011); Various State legislature laws and Insurance memos.

dence to support that young adults are more likely to be insured as a result of these policies, rather reallocation in the type of coverage. Specifically, they find that treated young adults are more likely to be covered as a dependent and less likely to be covered by their own employer-sponsored policy. The other study, by Levine et al. (2011), more fully exploits the potential impact of the policy by considering whether individuals were actually eligible within a state. Using a similar DD estimation strategy as Monheit et al. (2011), Levine et al. (2011) similarly find that individuals 19-24 years of age are not more likely to health insurance a coverages a result of the expanded coverage laws. However, when they interact their DD estimator with an indicator for eligibility they find a significant increase in insurance coverage for those who are eligible.

2.3 The Affordable Care Act

The Affordable Care Act was signed into law on March 23rd, 2010. This comprehensive health insurance reform is gradually rolling out over 2010-2013 before a large portion of the law is implemented in 2014. In addition to the expansion of dependent coverage, some of the enacted laws from the ACA that were implemented in 2010 include: small business health insurance tax credits, allowing states to cover more people on Medicaid by states receiving federal matching funds, expanding coverage for early retirees, providing access to insurance for those with pre-existing conditions (a more comprehensive law comes into place in 2014), free preventive care, eliminating lifetime limits on insurance coverage, regulating annual limits on insurance coverage and prohibiting denying coverage of children based on pre-existing conditions.

The ACA requires plans that offer dependent coverage to extend coverage to children under the age of 26 regardless of student status. Furthermore, both married and unmarried children can qualify for dependent coverage under a parent's policy. Prior to 2014, children under the age of 26 can only select coverage as a dependent on a parent's policy if they do not have their own employer-sponsored plan. However, in 2014 children can stay on their parent's employer plan even if they are able to receive coverage through their own employer. The law required all plans to adopt the expanded coverage when a plan renewed but no later than six months after the law was implemented on September 23rd, 2010.

With the expansion of dependent coverage under the ACA, the tax code was rewritten in the spring of 2010 to allow a dependent child who is under the age of 27 to receive health coverage on a tax-free basis. Therefore, a dependent child may receive tax-free coverage through the end of the calendar year in which the dependent turns 26. With the law signed in March and the tax code adjusted, Secretary of Health and Human Services, Kathleen Sebelius, called on leading insurance companies to cover young adults prior to the September 23rd implementation date. Specifically, she called on these companies to begin open enrollment in May suggesting that it would be costly to wait as insurance companies would have to unenroll those who were graduating from college and then re-enroll them in six months. Many of the nation's large insurance companies responded in accordance with the request.⁷

In all, the expansion of dependent coverage through the ACA is generally more expansive than the previously implemented state laws. For one, the state laws almost always used marital status as part of the eligibility criteria. In addition, the state laws only affected plans that were fully insured. The federal law through the ACA affects all employer-sponsored plans that provide dependent coverage, both self-insured and fully-insured plans. In the case when portions of an individual state law are more liberal than the federal law, it follows that the federal law is the minimum standard. For example, New York set a limiting age for dependent status to 30-years-old but required dependents to not be married. Therefore, plans that provide dependent coverage in New York now allow dependents to be married if they are under the age of 26 (federal law) but child dependents over the age of 26 and under the age of 30 must not be married to qualify.

A few papers have already begun to look at the affect of the ACA. Pohl (2011) considers the joint decision of single mothers to enter employment with mandated employer-sponsored insurance or take-up of expanded Medicaid. Antwi et al. (2012) analyze the effect of the ACA on the health insurance coverage rates of young adults. Antwi et al. (2012) provide the first stage effect of the policy implications of this paper by showing that both health insurance coverage and dependent coverage of treated young adults increases as a result of the ACA.

⁷See U.S. Department of Health and Human Services (2012) for a list of insurance companies who began enrollment prior to September 23rd, 2011

3 Health Insurance and Labor Supply

Prior literature on health insurance and employment has primarily focused on job mobility, single mothers on Medicaid, and spousal insurance coverage. Cooper and Monheit (1993) and Madrian (1994) find strong evidence of “job-lock” due to employer-sponsored health insurance. Strumpf (2011) uses variation in the states introduction of Medicaid in the 1960s and 1970s and finds no effect on labor force participation. However, Yelowitz (1995) finds that Medicaid expansion in the 1980s and 1990s that increased income limits and therefore reduced work disincentives caused an increase in labor force participation of single mothers. Pohl (2011) uses a structural model of labor supply to analyze how single mothers will respond to mandated employer-sponsored health insurance and expansions to Medicaid from the ACA. He projects that single mothers will significantly increase their participation in the labor market as a results of the health care reform.

A long string of literature has pointed to the fact that married women are likely to decrease their hours worked and labor force participation when they are able to receive health insurance through their husband’s plan. Buchmueller and Valletta (1999) find evidence that married women decrease their hours worked by 36 percent and they are 12 percent less likely to participate in the labor force. Royalty and Abraham (2006) extend the work of Buchmueller and Valletta (1999) by allowing the health insurance of both spouses to be endogenous. Therefore, the study considers the joint decision-making within households and finds that spousal insurance coverage has negative effects on working full-time.

The aim of this study is to understand how a policy to increase health insurance affects the labor market decisions of young adults. In a related study, Strumpf (2011) examines the introduction of the Medicaid program in the late 1960s and early 1970s and how it affected the labor supply decisions of single mothers. Strumpf (2011) finds no evidence that women who were eligible for Medicaid decreased their labor supply relative to women who were not eligible for Medicaid. Although the results are not statistically significant, the study finds that eligible single women may have actually increased their labor supply. These results are consistent with an alternative narrative that suggests that increased health benefits from Medicaid may offset incentives to decrease labor supply.

3.1 Theoretical Effects of Dependent Coverage on Labor Supply

Both Levine et al. (2011) and Monheit et al. (2011) suggest that young adults are more likely to be insured by dependent coverage as a result of expanded state coverage laws. In this section I discuss the theoretical predictions of expanding dependent health insurance coverage on the labor supply of young adults through a simple labor-leisure model. The labor-leisure model is a simplification of reality where workers have constraints on choosing hours, pay for some portion of employer-sponsored insurance, face frictions in the labor market, etc. Furthermore, the presented model does not address other partial and general equilibrium effects such as employer responses to state and federal policies to expand coverage as well as individual health effects.

Figure 4 shows the budget constraint, ABC, for a young adult who does not have health insurance coverage through either an employer or as a dependent. Budget constraint ABDE represents an individual who is employed by an employer who provides health insurance to full-time workers. The value of health insurance to the employee is measured by the length of the line segment BD. The three indifference curves represent three potential individuals with different preferences. Individual 0, represented by U_0 , prefers to work above the minimal hours required to receive the employer-sponsored insurance. Individual 1, represented by U_1 , has positive value for health insurance and works the least amount of hours to still qualify for health insurance, suggesting the existence of a “Health Insurance Notch”. Individual 2, represented by U_2 , is unaffected by an employer who provides insurance.

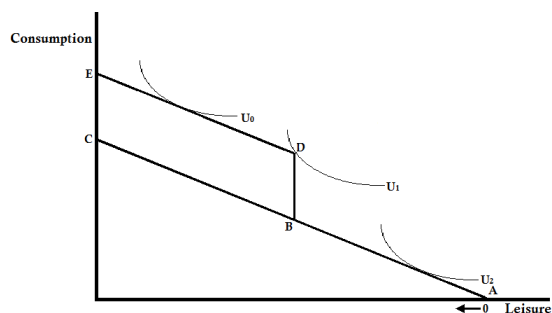


Figure 4: Prior to Expanding Dependent Coverage

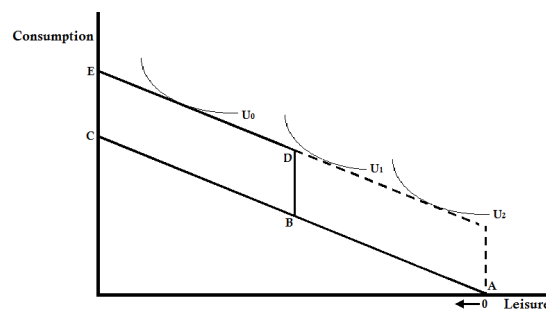


Figure 5: After Expanding Dependent Coverage

Figure 5 shows the new budget constraint when these three representative individuals receive health insurance from an outside source such as dependent coverage through a parent. Individual 0 does not adjust his labor supply, individuals 1 and 2 both decrease their labor supply and obtain a higher level of utility. Although the model is quite simple it outlines two important insights: 1) if an individual does not value health insurance ($BD = 0$) then their labor supply will not be affected by receiving coverage as a dependent. 2) Conditional on having a positive value for health insurance, only those who have preferences at the “Health Insurance Notch” or to the right of it will adjust their labor supply when they are able to receive coverage as a dependent.

Table 2: Summary of SIPP Panels

Panel	Date of First Interview	Date of Last Interview	# of Wave 1 Eligible HHs	# of Waves	# of Unique Obs. Ages 19-29 in Analysis
2001	February 01	January 2004	50,500	9	19,373
2004	February 04	January 2008	51,379	12	25,126
2008	September 08	December 2012 ^a	52,031	13	24,155

^a Current data release goes through November 2011 (Wave 10).

^b Source: Westat (2009)

4 Data

The primary data sources for this paper are the 2001, 2004 and 2008 panels of the Survey of Income and Program Participation (SIPP) (U.S. Census Bureau 2012). The survey design of the SIPP is a continuous series of national panels. The same households are surveyed every 4 months for a range of two and half to four years. The variables used in the analysis come from the core questions asked in each survey. Respondents then recall the information for the prior four months to provide monthly data. Interviews with respondents are conducted by both personal visits and telephone. Table 2 reports the details of the three panels used in the study.

SIPP provides important advantages relative to the Current Population Survey (CPS) that was used by Monheit et al. (2011) and Levine et al. (2011). The key advantage of SIPP over the CPS is the detail of the health insurance information. The March supplement of the CPS simply asks individuals about their health insurance last year. This results in some confusion in the response of individuals in reporting either their current health insurance status, their status for the last 12 months, or their status for the last calendar year.

Table 3 provides summary statistics for individuals aged 19-25. Reported in Table 3 are a few of the outcome variables analyzed in this paper. In the 2001 panel there are 13,559 unique individuals between the ages of 19-25. The 2004 panel has 18,141 unique individuals in this age group. The 2008 panel has 14,076 unique individuals prior to the enactment of the ACA and 10,288 unique individuals after the ACA enactment. Changes in dependent health insurance are the mechanism of interest, which is hypothesized to affect the labor market decisions and social behavior of young adults. Table 3 clearly shows an increase in dependent coverage for both males and females after

the ACA was implemented. However, it appears that the health insurance coverage rate has not changed, a finding that suggests that individuals may just be reallocated from their own plan to their parents. In addition, Table 3 shows that after the ACA was implemented females and males were more likely to be full-time students, less likely to be married, and less likely to participate in the labor force. The remainder of this paper explores the extent to which policies that expanded dependent coverage can alter individual labor market and lifestyle decisions.

Table 3: Summary Statistics

	Females	Males
	Mean	Mean
2001 Panel: N=13,559		
Any Health Ins.	0.73	0.65
Private Health Ins.	0.60	0.61
Dependent Health Ins.	0.25	0.25
Full-Time Student	0.30	0.27
Married	0.26	0.17
Labor Force Part.	0.74	0.83
2004 Panel: N=18,141		
Any Health Ins.	0.76	0.67
Private Health Ins.	0.61	0.62
Dependent Health Ins.	0.25	0.25
Full-Time Student	0.32	0.30
Married	0.22	0.14
Labor Force Part.	0.76	0.83
2008 Panel Before ACA: N=14,076		
Any Health Ins.	0.71	0.61
Private Health Ins.	0.55	0.54
Dependent Health Ins.	0.27	0.27
Full-Time Student	0.35	0.32
Married	0.21	0.12
Labor Force Part.	0.73	0.80
2008 Panel After ACA: N=10,288		
Any Health Ins.	0.73	0.67
Private Health Ins.	0.58	0.59
Dependent Health Ins.	0.35	0.35
Full-Time Student	0.40	0.35
Married	0.16	0.10
Labor Force Part.	0.69	0.75

5 State Policies to Expand Dependent Coverage To Young Adults

The aim of this paper is to identify the effect of expanding dependent health insurance coverage on the labor market decisions of young adults. To identify the causal effect of expanding dependent coverage I must control for systematic shocks to the labor market that may be correlated with the policy change of a state. The changes in state policies to expand dependent coverage from the years 2001 to 2010 provide a very suitable setting to identify the causal effect for two reasons: 1) states implemented the policies to expand coverage at different points in time. Therefore, after conditioning for year fixed effects, it is of less concern that systematic time shocks are driving changes in labor force decisions for treated and non-treated states. 2) The eligibility requirements for a dependent to be treated by the policy varied across states. This variation in state eligibility requirements allows me to condition out contemporaneous effects that may be specific to certain groups of the young adult population. In all, this across-state and across-time variation provides a robust estimation setting to reassure that the results from the state policy changes are being driven from the actual policy to expand coverage and not contemporaneous effects. The estimation strategy employs the difference-in-difference-in-difference (DDD) framework. In the remainder of this section I present the identification strategy and estimate the effect of the state laws on health insurance, labor market decisions, student status and marital outcomes. I then analyze the identification environment that the state laws provide by testing for internal threats to the identification framework. I conclude the section by providing a falsification test and a robustness check.

5.1 State Policy Identification Strategy

To estimate the effect of expanding dependent coverage, I exploit the variation of policy implementation and eligibility requirement by comparing the change in outcomes of individuals who were eligible in states that have implemented a policy to expand coverage (treated group) to individuals within the same state who were not eligible for the policy (control group). In addition, I control for differences in young adults in non-treated states (those who did not adopt a policy to expand dependent coverage) who have characteristics that would either classify them as eligible or ineligible.

This estimation strategy is the difference-in-difference-in-difference framework that is similar to other labor- and health-related studies such as Gruber (1994) and Strumpf (2011), to name a few. The DDD framework makes fewer assumptions than the commonly used DD estimation strategy. While the DD estimator requires strict assumptions on the pre-treatment trends of the control and treated groups, the identification assumption of the DDD estimator is that there exists no contemporaneous shock that affects the relative outcomes of the eligible group in the same state-years as the law (Gruber 1994).

The general DDD regression equation for individual i with eligibility e in state s at time t is

$$y_{iest} = \alpha_{te} + \theta_{se} + \delta_{ts} + \tau(\text{eligible}_{iest} \times \text{law}_{st}) + X_{iest}\beta + \varepsilon_{iest}. \quad (1)$$

The coefficient of interest is τ , the DDD parameter. eligible_i is an indicator that takes the value of one for an individual who is eligible and law_{st} is an indicator that takes the value of one for a state that has the expanded coverage law in place at time t . X_{ist} is vector of observable characteristics specific to the individual. ε_{ist} is an unobserved term specific to the individual that affects the outcome. α_{te} is an eligibility-year fixed effect, θ_{es} is an eligibility-state fixed effect and δ_{ts} is a year-state fixed effect. The inclusion of these three sets of fixed effects eliminate the regular level fixed effects which are in other DDD models that do not have multiple treatment periods.⁸

The DDD strategy outlined in equation 1 is similar to other studies that are able to classify individuals in non-treated states as either eligible or non-eligible. In this study, the definition of eligibility is unclear for states who did not implement a policy change. Therefore, to obtain the DDD estimate I must flexibly control for the characteristics that determine eligibility status in a state. This is done by interacting each component of equation 1 that contains eligibility with the characteristics that define eligibility within a state (age, full-time student status, marital status, and whether the dependent has children). By incorporating these interaction terms the regression

⁸See Wooldridge and Imbens (2007) for a more complete discussion of DDD models with multiple groups and time periods.

equation of interest is

$$\begin{aligned}
 y_{iamkfst} &= \alpha_{ta} + \alpha_{tm} + \alpha_{tk} + \alpha_{tf} + \theta_{sa} + \theta_{sm} + \theta_{sk} + \theta_{sf} + \delta_{ts} \\
 &\quad + \tau(\text{eligible}_{iamkfst} \times \text{law}_{st}) + X_{iamkfst}\beta + \nu_{st} + \varepsilon_{iamkfst}.
 \end{aligned} \tag{2}$$

α_{ta} , α_{tm} , α_{tk} and α_{tf} are the time by eligibility fixed effects where a represents age, m represents marriage, k represents children and f represents full-time student. Similarly, θ_{sa} , θ_{sm} , θ_{sk} and θ_{sf} are the state by eligibility fixed effects. I choose to write equation 2 without fully interacting the DDD estimator because I am interested in the average treatment effect over the eligibility criteria. Included in the vector of observed characteristics, X , are race, part-time student status, work disability, the level and square of household income above the poverty line, and education level fixed effects. Because I follow the same individuals over time, the error terms for an individual are not independent. To account for this correlation, I cluster the standard errors on the individual.

5.2 Impact on Health Insurance Coverage

The studied mechanism that causes individuals to adjust their labor supply are the expanded dependent coverage laws that increase their propensity to have dependent coverage. Specifically, young adults who are affected by the policy may not actually be insured at a higher rate, rather they are more likely to be insured as a dependent. To test this I estimate two DDD models using young adults age 19-29 years old. The first model only uses age as the eligibility factor. The second model incorporates all the eligibility criteria.

The studies of Levine et al. (2011) and Monheit et al. (2011) suggest that I should find that eligible individuals treated by the policy are more likely to be insured as a dependent. However, it is not clear whether I will find that eligible individuals treated by the policy are more likely to be insured in general. This study adds to the work of Levine et al. (2011) and Monheit et al. (2011) by providing additional evidence of the effect of these state laws on health insurance outcomes. Neither of the two previous studies used the full horizon of state laws prior to the ACA in their analysis. Because I use state laws until the implementation of the ACA, this analysis incorporates

almost twice as many states that have implemented laws than the studies of Levine et al. (2011) and Monheit et al. (2011).⁹

Table 4 displays the results for the DDD model for both males and females in which age is the only criteria used to determine eligibility. I find no effect of the policy on the health insurance coverage rate. However, the simple assignment of all individuals who satisfy the age criteria to treatment causes significant measurement error. The model is assigning treatment to individuals who did not actually meet the eligibility criteria and were therefore not affected by the policy change. In addition, these policies only affected individuals who had a parent with employer-sponsored insurance at a fully-insured firm. Therefore, there is over assignment of treatment, i.e. an intent-to-treat framework. The resulting measurement error on the point estimates in Table 4 is not straight forward. In Appendix section A I show that the measurement error will only attenuate the point estimates on the treatment variable. Therefore, the DDD estimates in Table 4 are likely biased towards zero. However, Table 4 does show a statistically significant effect at the 5 percent level on dependent coverage for females.

By using the full set of eligibility criteria I find a significant effect on coverage as a dependent. Eligible females are 5.6 percentage points more likely to be covered as dependent and males are 3.3 percentage points more likely to be covered as a dependent. Table 5 reports the point estimates and the standard errors that show the DDD coefficients for dependent coverage are statistically significant at the 1 percent level. In addition, the DDD point estimate for any health insurance coverage is statistically significant at the 1 percent level for males. However, these results also suffer from measurement error that attenuate the DDD estimates. The measurement error is not as severe as the estimates in Table 4 because these estimates incorporate the full set of eligibility criteria. However, there is still over assignment of treatment because I am unable to identify which individuals had parents who worked at a firm with employer-sponsored insurance that was not self-insured. In general, these results are consistent with the previous work of Levine et al. (2011) and Monheit et al. (2011) by showing an increase in the rate of dependent coverage. However, it remains inconclusive whether these expanded coverage laws increase the health insurance rate of

⁹Both Levine et al. (2011) and Monheit et al. (2011) use the March Supplement of the Current Population Survey.

Table 4: State Policy-Eligibility (Age Only) Diff-in-Diff-in-Diff Estimates: Health Insurance Coverage

	<u>Females</u>			<u>Males</u>		
	Any Coverage	Private Coverage	Dependent Coverage	Any Coverage	Private Coverage	Dependent Coverage
DDD	0.0193 (0.0143)	0.0009 (0.0150)	0.0233** (0.0103)	0.0174 (0.0157)	0.0114 (0.0157)	0.0047 (0.0104)
Married	0.0352*** (0.0053)	0.0846*** (0.0058)	-0.0887*** (0.0035)	0.1109*** (0.0065)	0.1155*** (0.0066)	-0.0632*** (0.0037)
Full-Time Student	0.0791*** (0.0051)	0.1096*** (0.0056)	0.2250*** (0.0051)	0.1272*** (0.0059)	0.1222*** (0.0062)	0.2568*** (0.0055)
Part-Time Student	0.0325*** (0.0060)	0.0405*** (0.0066)	0.0067 (0.0048)	0.0664*** (0.0076)	0.0619*** (0.0078)	0.0448*** (0.0064)
Children	0.0626*** (0.0046)	-0.0067 (0.0050)	0.0374*** (0.0038)	0.0393*** (0.0054)	0.0260*** (0.0054)	0.0477*** (0.0042)
Work Disability	0.1279*** (0.0088)	-0.1467*** (0.0096)	0.0151** (0.0072)	0.1460*** (0.0108)	-0.1560*** (0.0110)	0.0279*** (0.0078)
White	-0.0147*** (0.0055)	0.0671*** (0.0062)	0.0359*** (0.0046)	0.0313*** (0.0067)	0.0580*** (0.0068)	0.0257*** (0.0048)
Poverty Ratio	0.0433*** (0.0018)	0.0744*** (0.0029)	0.0337*** (0.0016)	0.0464*** (0.0019)	0.0566*** (0.0023)	0.0257*** (0.0010)
Poverty Ratio-Sq.	-0.0011*** (0.0001)	-0.0020*** (0.0002)	-0.0007*** (0.0001)	-0.0010*** (0.0001)	-0.0013*** (0.0001)	-0.0005*** (0.0000)
N	594548	594548	594548	563936	563936	563936

^a Included fixed effects for all regressions: Education Level, Year-Age, State-Age, and State-Year.

^b Standard errors clustered on the individual are presented in parentheses.

^c * 0.10, ** 0.05 and ***0.01 denote significance levels.

Table 5: State Policy-Eligibility (Age, Student, Marriage, and Children) Diff-in-Diff-in-Diff Estimates: Health Insurance Coverage

	<u>Females</u>			<u>Males</u>		
	<u>Any Coverage</u>	<u>Private Coverage</u>	<u>Dependent Coverage</u>	<u>Any Coverage</u>	<u>Private Coverage</u>	<u>Dependent Coverage</u>
DDD	0.0161 (0.0125)	0.0083 (0.0131)	0.0557*** (0.0101)	0.0382*** (0.0133)	0.0324** (0.0132)	0.0331*** (0.0099)
Part-Time Student	0.0319*** (0.0060)	0.0393*** (0.0065)	0.0046 (0.0048)	0.0658*** (0.0076)	0.0610*** (0.0078)	0.0438*** (0.0063)
Work Disability	0.1287*** (0.0088)	-0.1449*** (0.0096)	0.0148** (0.0072)	0.1473*** (0.0108)	-0.1547*** (0.0108)	0.0286*** (0.0076)
White	-0.0138** (0.0055)	0.0669*** (0.0062)	0.0359*** (0.0046)	0.0307*** (0.0066)	0.0576*** (0.0067)	0.0264*** (0.0048)
Poverty Ratio	0.0433*** (0.0018)	0.0743*** (0.0029)	0.0335*** (0.0016)	0.0462*** (0.0018)	0.0563*** (0.0023)	0.0254*** (0.0010)
Poverty Ratio-Sq.	-0.0011*** (0.0001)	-0.0020*** (0.0002)	-0.0007*** (0.0001)	-0.0010*** (0.0001)	-0.0012*** (0.0001)	-0.0005*** (0.0000)
N	594548	594548	594548	563936	563936	563936

^a Included fixed effects for all regressions: Education Level, State-Year, Year-Age, Year-Married, Year-Student, Year-Children, State-Age, State-Married, State-Student, and State-Children.

^b Standard errors clustered on the individual are presented in parentheses.

^c * 0.10, ** 0.05 and ***0.01 denote significance levels.

the targeted populations.

5.3 Labor Market Outcomes

The results found in Table 5 are the first stage effects of the policy. They show that individuals have an increased propensity to have dependent coverage and therefore may alter their labor supply. To estimate the effect of the expanding dependent coverage on the labor supply of young adults I follow the identification strategy presented in section 5.1. I estimate equation 2 where the dependent variable is a measure of an individual's labor market outcome. Again, I estimate the regression equation separately for males and females and use the SIPP data of individuals 19-29 years-old. I use six separate labor market indicators: labor force participation, full-time employment, usual hours worked per week, current employment, number of jobs in the month, and the proportion of the month employed.

The reported DDD estimates in Table 6 show that the expanded dependent coverage laws had

significant effects in the labor market. The top panel of the Table 6 reports the DDD estimates for females and the bottom panel of the table reports the DDD estimates for males. The expanded dependent coverage laws decreased labor force participation for eligible females by 4.6 percentage points. The effect on males was much smaller in magnitude, 1.7 percentage points. The point estimate for females is statistically significant at the 1 percent level and the point estimate for males is statistically significant at the 10 percent level. Furthermore, Table 6 shows the robustness of this finding over a number of labor market outcomes. For females there is statistically significant decreases in full-time employment, hours worked, employment rate, number of jobs per month, and the proportion of the month employed. I find similar qualitative results for males, but the effect on hours worked is not statistically different from zero. Similar to labor force participation, the magnitude of the effect of the policy on these different labor market outcomes are larger for females than males. These differences are likely due to the results in Table 5 that show that the effect on dependent coverage for females was nearly twice as large as males. One potential explanation for the difference is that females have a greater value for health insurance and are more likely to be positioned at the “health insurance notch.” This higher value of health insurance for females results in females having higher expected health care costs during this age range. To my knowledge, this is the first set of evidence to suggest that health insurance plays an important role in the employment decisions of young adults. Gruber and Madrian (2002) provide a critical survey of the health insurance and labor supply literature and conclude that health insurance provides an important role in the labor decisions of secondary earners, however, there is a lack of evidence for other groups such as young adults.

5.4 Education and Marriage Outcomes

Table 6 shows that these state policies altered the labor supply decision of young adults. The question remains whether these individuals reinvested in human capital through college enrollment. Similarly, understanding the impact these policies had on the structure of the family is important to policy makers. The marginal benefit of marriage may diminish for a young adult who now can receive coverage from a parent instead of through a spouse. In this section I estimate the extent to

Table 6: State Policy-Eligibility Diff-in-Diff-in-Diff Estimates: Employment Outcomes

	LFP	Full-Time Employment	Hours Worked	Employed	# of Jobs	Time Employed
Females:						
DDD	-0.0455*** (0.0121)	-0.0605*** (0.0124)	-2.8240*** (0.5578)	-0.0385*** (0.0129)	-0.0629*** (0.0168)	-0.0390*** (0.0129)
N	594548	594548	594548	594548	594548	594548
Males:						
DDD	-0.0165* (0.0096)	-0.0255** (0.0113)	-0.9114 (0.5769)	-0.0191* (0.0109)	-0.0269* (0.0160)	-0.0217* (0.0112)
N	563936	563936	563936	563936	563936	563936

^a Standard errors clustered on the individual are presented in parentheses.

^b * 0.10, ** 0.05 and ***0.01 denote significance levels.

which treatment caused an individual to change their decision to be enrolled in school as a full-time student and/or delay or forgo marriage. To do this I estimate equation 2 for these two outcomes and I exclude states that required the dependent variable as part of the eligibility criteria.¹⁰

Table 7 reports the DDD estimates for both females in the top panel and males in the bottom panel. The first column presents the DDD estimates for full-time student status, the second column reports the DDD estimates for part-time student status, and the third column reports the DDD estimates for marital status. In addition to marriage, column four contains the DDD estimates for the effect of the policy on cohabitation.

As a result of an expanded coverage law, Table 7 shows that eligible females were 3.2 percentage points more likely to be a full-time student. This result is statistically significant at the 5 percent level. Although the point estimate for males suggests an increase in full-time student status, the result is not statistically significant at the 10 percent level. I find no statistical effect on part-time student status, marital status, or cohabitation for either genders. However, the sign for the marriage and cohabitate specifications suggests that treated individuals may have been less likely to be married and more likely to cohabitate after the policy. It is not a surprise to find no evidence that suggests that marriage rates were affected by the state policies. Because I limit the data to

¹⁰For estimating the effect on full-time student status I therefore *exclude* Idaho, Illinois, Iowa, Rhode Island, South Dakota, and Virginia. For estimating the effect on marital status I only *include* non-policy states and Indiana, Massachusetts, South Dakota, Tennessee, and Virginia. This limited number of policy states provides a weak identification environment to test the impact of these policies on the marriage rate.

Table 7: State Policy-Eligibility Diff-in-Diff-in-Diff Estimates: Student and Marriage

	Full-Time Student	Part-Time Student	Married	Cohabitate
Females:				
DDD	0.0321** (0.0150)	-0.0103 (0.0116)	-0.0145 (0.0314)	0.0136 (0.0208)
N	329487	329487	263717	263717
Males:				
DDD	0.0213 (0.0160)	-0.0071 (0.0109)	-0.0215 (0.0286)	0.0165 (0.0212)
N	302784	302784	251773	251773

^a Full-time and part-time student specifications excluded states:Idaho, Illinois, Iowa, Rhode Island, South Dakota, Virginia and all states who did not enact a policy.

^b Married and cohabitate specification included states: Indiana, South Dakota, Tennessee, and Virginia.

^c Standard errors clustered on the individual are presented in parentheses.

^d * 0.10, ** 0.05 and ***0.01 denote significance levels.

states that did not require individuals to be single, the identification framework does not provide the statistical power to convincingly test this outcome.¹¹

5.5 Threats to Internal Validity of the DDD Framework

In effort to understand whether the estimated results can be interpreted as causal, I analyze the identification environment that the state policies provide in two ways. First, I look at the endogenous timing of these state policies and how it may affect the interpretation of the main results. Second, to be affected by the policy one needed to satisfy the eligible criteria set by the state. The age limit is exogenous to the individual. However, an individual may choose to attend school, delay marriage, or alter their decision to have children in order to meet the eligibility criteria. Therefore, in Section 5.5.2 I estimate the effect of the policy on selection into the three potential endogenous eligibility criteria. The difference between Sections 5.5.2 and 5.4 is that Section 5.5.2 analyzes selection into treatment and Section 5.4 analyzes changes as a result treatment. The variation in eligibility criteria across states allows me to separately identify these two effects.

¹¹Because of the larger health care reform in Massachusetts that coincided with their law to expand dependent coverage, I drop all observations from this state and find very similar results to those presented in Tables 5, 6, and 7.

5.5.1 Potential Endogeneity of the Timing of State Policies

The identifying assumption of the DDD framework is that there exists no contemporaneous shocks that affect the outcomes of eligible young adults relative to non-eligible young adults in the same years in the state when the policy is in effect. This assumption is violated if the incidence of policy adoption is predicated on the characteristics of eligibles relative to non-eligibles. Specifically, if states adopt a policy because of an increase in the relative uninsured rate between eligible and non-eligible young adults, then the policy adoption is not exogenous and the results from the DDD are not interpreted as causal. Besley and Case (2000) highlight this point within the difference-in-difference (DD) framework. The DDD framework provides much greater ability, relative to the DD framework, to overcome this potential endogeneity problem.

To analyze the incidence of endogenous policy adoption I examine whether observable characteristics of eligibles relative to non-eligibles were significant predictors of new laws to expand dependent coverage (Strumpf 2011). To do this I use time-variant data at the state level. The dependent variable for each state by time observation is an indicator for whether a state has an expanded dependent coverage law, as shown in Table 1. The independent variables of interest are the difference in the health insurance rate between eligibles and non-eligibles and the difference in the labor force participation rate between eligibles and non-eligibles. I include the relative health insurance rate rather than the relative child dependent insurance rate because it was the former that policy makers were aiming to influence. I include the relative labor force participation rate to test whether policy makers endogenously implemented policy with the foresight of affecting employment rates of eligibles. In addition, I control for the state unemployment rate, year fixed effects, and state fixed effects.

Table 8 reports the results from six separate regressions where each regression is weighted by the 2005 state population of 19-25 year-olds. The first three columns report the coefficients for the difference in the health insurance rate and labor force participation rate between eligibles and non-eligibles using various lags. Columns four through six use the ratio between eligibles and non-eligibles for the health insurance rate and labor force participation rate using various lags. Most policies were proposed and accepted by the state legislatures between one to three years prior to

Table 8: Determinants of Implementing Expanded Dependent Coverage Policy

	Difference			Ratio		
	Lagged (1)	Lagged (2)	Lagged (3)	Lagged (1)	Lagged (2)	Lagged (3)
Health Insurance	-0.1711 (0.1916)	0.0660 (0.2725)	0.3887 (0.3253)	-0.1334 (0.1368)	0.0448 (0.2032)	0.3032 (0.2534)
Labor Force Part.	-0.0184 (0.3866)	0.0530 (0.3692)	0.1506 (0.3474)	0.0447 (0.3239)	0.0880 (0.3272)	0.1079 (0.2997)
Unemployment Rate	-0.0281 (0.0310)	-0.0478 (0.0347)	-0.0057 (0.0489)	-0.0291 (0.0309)	-0.0482 (0.0350)	-0.0037 (0.0491)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	0.41	0.05	1.05	0.48	0.07	0.99
R-squared	0.269	0.302	0.385	0.270	0.302	0.385

^a Standard errors clustered at the state level are presented in parentheses.

^b Each regression is weighted by the state population of 19-25 year olds.

^c The reported F-Stat is from the joint exclusion test of health insurance and labor force participation.

their implementation, therefore, I lag the independent variables accordingly. Column (1) presents the results for a first lag, column (2) presents second lag results, and column (3) presents third lag results.

The results show that neither the relative health insurance coverage rate nor the relative labor force participation rate is a statistically significant predictor of policy adoption. To further test this I report the results of a F-test on the joint exclusion of both these estimates. The results from the F-test also do not provide evidence of endogenous policy adoption. Therefore, the timing of policy implementation was plausibly idiosyncratic to the eligible group relative to the non-eligible group. However, if other state programs that affect the labor supply of eligible individuals relative to ineligible individuals are correlated with policy adoption then the DDD strategy will be compromised. In section 5.6 I present the results of a falsification test that would likely exploit additional endogeneity that may exist.

5.5.2 Potential Endogeneity of Eligibility

Table 1 shows that the eligibility criteria varied across states. While the age limit is not adjustable for an individual, the other three categories are adjustable and thus could lead to endogenous

selection into treatment. To address concerns that some individuals are selecting into treatment, I estimate regressions for selection on full-time student status, not being married, and not having children.

To analyze selection into full-time student status I limit the data to the six states who implemented a policy to expand dependent coverage and who also required eligible individuals to be full-time students. I then estimate the following equation for individual i , in state s , at time t ,

$$student_{ist} = \alpha TreatGroupF_{ist} + \gamma(TreatGroupF_{ist} \times Law_{st}) + X_{ist}\beta + \nu_{ist} \quad (3)$$

where $student_{ist}$ takes the value of one if the individual is a full-time student and zero otherwise. $TreatGroupF_{ist}$ takes the value of one if individual i meets the marriage and children criteria of the state. Law_{st} takes the value of one if the law is in affect in state s at time t . X_{ist} is a vector that includes an indicator for education level, race and work disability. Also included is the level and square of the family income level above the poverty threshold as well as the following fixed effects: state-year, state-age, state-married, state-children, year-age, year-married, and year-children. ν_{ist} is an unobserved term that affects student status and is assumed to be uncorrelated with the interaction of Law and $TreatGroupF$. The estimate of interest, $\hat{\gamma}$, is the commonly known DD estimate. If γ is greater than zero it indicates that individuals who meet the other eligibility criteria are more likely to be full-time students when the policy is implemented and thus may be endogenously selecting because of the policy.

The other two regression equations for the marital choice and the choice to have children are

$$married_{ist} = \alpha TreatGroupM_{ist} + \gamma(TreatGroupM_{ist} \times Law_{st}) + X_{ist}\beta + \nu_{ist}, \quad (4)$$

$$children_{ist} = \alpha TreatGroupK_{ist} + \gamma(TreatGroupK_{ist} \times Law_{st}) + X_{ist}\beta + \nu_{ist}. \quad (5)$$

Similarly, each regression is limited to states who implemented a policy to expand dependent coverage and who also required eligible individuals to not be married, for equation 4, and not have children, for equation 5. $TreatGroupM_{ist}$ takes the value of one if individual i meets the full-time

Table 9: Diff-in-Diff Estimates: Eligibility Selection

	Student ^b	Married ^c	Have Children ^d
Females			
$\hat{\tau}_{DD}$	-0.0017 (0.0346)	-0.0268 (0.0180)	0.0500 (0.0615)
N	40038	330831	63003
Males			
$\hat{\tau}_{DD}$	-0.0029 (0.0308)	-0.0079 (0.0163)	0.0183 (0.0621)
N	36646	312163	61089

^a Included fixed effects for all specifications: Education Level, State-Age, Year-Age, State-Year. Included regressors for all specifications: work disability, white, and the level and square of family income above poverty threshold.

^b Additional included fixed effects: Year-Married, Year-Children, State-Married and State-Children.

^c Additional included fixed effects: Year-Student, Year-Children, State-Student and State-Children.

^d Additional included fixed effects: Year-Married, Year-Student, State-Married and State-Student.

^e Standard errors clustered individual are presented in parentheses.

^f * 0.10, ** 0.05 and ***0.01 denote significance levels.

student and children criteria of the state and $TreatGroupK_{ist}$ takes the value of one if individual i meets the full-time student and marriage criteria of the state.

Table 9 presents the results for the estimated difference-in-difference coefficient from equations 3, 4 and 5 for both males and females. Standard errors are clustered on the individual and are in parenthesis. The results in Table 9 provide no statistical evidence that individuals were selecting into treatment. Not only are the associated t-statistics small, but the point estimates are also small. However, the signs on the estimated coefficients on the DD estimator for the full-time student and marriage specifications are in the direction that suggests selection may have occurred. If selection into treatment did occur, the results provide what I refer to as the “social effect” or the “policy effect.” Meaning that these policies may have caused individuals to adjust their student, marriage, and/or children decisions that eventually resulted in these individuals being affected by the policy.

Table 10: Falsification Test: Employment, Education and Marriage Outcomes

	LFP	Full-Time Employment	Hours Worked	Employed	# of Jobs	Time Employed
Females:						
DDD	-0.0293 (0.0247)	-0.0110 (0.0279)	-0.5358 (1.2183)	-0.0162 (0.0259)	-0.0292 (0.0366)	-0.0140 (0.0263)
N	188034	188034	188034	188034	188034	188034
Males:						
DDD	-0.0062 (0.0166)	-0.0065 (0.0240)	-0.1547 (1.3466)	0.0006 (0.0194)	-0.0141 (0.0338)	-0.0031 (0.0208)
N	171535	171535	171535	171535	171535	171535

	Full-Time Student	Part-Time Student	Married	Cohabitate
Females:				
DDD	0.0153 (0.0177)	-0.0241 (0.0164)	0.1707 (0.1469)	-0.0043 (0.0735)
N	163148	163148	96196	96196
Males:				
DDD	0.0146 (0.0184)	0.0097 (0.0144)	0.0129 (0.2009)	-0.0676 (0.1022)
N	149243	149243	87948	87948

^a Standard errors clustered on the individual are presented in parentheses.

^b * 0.10, ** 0.05 and ***0.01 denote significance levels.

5.6 Falsification Test

To ensure that contemporaneous effects are not driving the results, I present a simple falsification test. I re-estimate equation 2 for the outcomes of interest but limit the data used in the analysis to individuals under the age of 30 years-old and over the maximum of either the age limit of the state or 26 years-old. Therefore, I am only estimating equation 2 using individuals who should not be effected by the policy. Furthermore, I assign treatment based on state requirement for student-status, marital status, and whether one has children. Therefore, if the results are simply an artifact of the control groups then the results from the falsification test should be significantly different from zero. Table 10 provides the DDD estimates for the labor market outcomes, education outcomes, and marriage outcomes.

Table 11: Recession Robustness DDD Estimates: Labor Market Outcomes

	LFP	Full-Time Employment	Hours Worked	Employed	# of Jobs	Time Employed
Females:						
DDD	-0.0672*** (0.0202)	-0.0673*** (0.0206)	-3.7744*** (0.9444)	-0.0610*** (0.0212)	-0.0972*** (0.0278)	-0.0529** (0.0212)
N	446875	446875	446875	446875	446875	446875
Males:						
DDD	-0.0202 (0.0154)	-0.0332* (0.0180)	-1.5356 (0.9599)	-0.0282* (0.0169)	-0.0511** (0.0259)	-0.0367** (0.0173)
N	421021	421021	421021	421021	421021	421021

^a Standard errors clustered on the individual are presented in parentheses.

^b * 0.10, ** 0.05 and ***0.01 denote significance levels.

The results from the falsification test provide convincing evidence that contemporaneous effects through the control groups are not driving the results. In addition to the point estimates being statistically insignificant, the economic significance is small for most outcomes. In all, these outcomes reinforce the previous findings that employment outcomes and full-time student status of young adults are affected by laws to expand dependent coverage and not by spurious affects from the control group.¹²

5.7 Recession Effect

One concern is that a large number of states implemented policies at the end of the decade and therefore if young adults behave differently during the a weak economy then the results may be driven by the recession and not by the state polices to expand health insurance. Specifically, the DDD estimation strategy is compromised by shocks that are correlated with the timing of policy implementation that affect the eligible individuals differently than the non-eligible individuals. To ensure that the *Great Recession* is not driving the results, I re-estimate the DDD model for only the years 2000 through 2007.

Table 11 shows similar results to those presented in Table 6. It is interesting to note that the magnitudes of the point estimates prior to the recession are slightly larger for both females and

¹²Using the same falsification test I found no affect on the dependent health insurance coverage rate.

Table 12: Recession Robustness DDD Estimates: Education and Marriage Outcomes

	Full-Time Student	Part-Time Student	Married	Cohabitate
Females:				
DDD	0.0459* (0.0254)	-0.0141 (0.0218)	-0.0336 (0.0822)	0.0660 (0.0467)
N	247803	247803	196622	196622
Males:				
DDD	0.0056 (0.0283)	0.0110 (0.0201)	0.0231 (0.0843)	0.0518 (0.0434)
N	226143	226143	186785	186785

^a Full-time and part-time student specifications excluded states: Idaho, Illinois, Iowa, Rhode Island, South Dakota, Virginia and all states who did not enact a policy.

^b Married and cohabitate specification included states: Indiana, South Dakota, Tennessee, and Virginia.

^c Standard errors clustered on the individual are presented in parentheses.

^d * 0.10, ** 0.05 and ***0.01 denote significance levels.

males. This is likely due to the fact that it was easier for young adults to gain employment prior to the *Great Recession* and therefore they were more likely to be participating in the labor market when their state implemented a policy. The education and marriage results presented in Table 12 are similar to the results presented in Table 7. For females, the point estimate for full-time student status is statistically significant at the 10 percent level and is not statistically different from the point estimate found in Table 7.

6 The Affordable Care Act

Estimating the effect of expanded dependent health insurance coverage on the labor market decisions of young adults from the state policies had both its advantages and disadvantages. One shortcoming of the analysis in section 5 was potential for individuals to select into treatment by attending school or delaying marriage. Eligibility under the ACA is only determined through age and therefore selection issues through student status or marital status are not a problem. However, because the ACA was a national policy all states were effected and therefore I am not able to use the difference-in-difference-in-difference estimation strategy. Instead, I use the difference-in-difference framework to measure the change in outcomes of those who are effected by the policy relative to the change in outcomes of those who were not effected by the policy. In addition, estimating the effect of expansion of dependent coverage from the ACA alleviates a majority of the measurement error problem. Under the ACA, all firms who offer dependent coverage are now required to expand coverage of child dependents up to age 26. The remaining measurement error only enters through assigning treatment to an individual who is not effected because they do not have a parent with employer-sponsored insurance.

The ACA was passed into law in March of 2010 and the expanded dependent coverage took affect on September 23rd, 2010. However, one caveat to the timing of the law implementation is that Secretary of Health and Human Services, Kathleen Sebelius, asked leading insurance companies to begin covering young adults in May of 2010. A large number of the major health insurance coverage beckoned to the call and immediately began allowing young adults under the age of 26 to be covered by their parent's health insurance plan. Figures 6, 7, 8, and 9 show that the increase in health insurance rates began around May of 2010 (first vertical line) and continued through the rest of the year. For this reason, I choose to drop all observations between May 1st, 2010, and September 30, 2010.

6.1 ACA Identification Strategy

To estimate the effect of expanding dependent coverage from the ACA I compare the change in outcomes of 19-25 year-olds (treated group) to the change in outcomes of 26-29 year-olds (control

group). This is a similar identification strategy used by Antwi et al. (2012) and therefore I expect to find similar results in health insurance coverage. The DD estimation strategy is more restrictive than the DDD strategy in section 5. An important assumption is the treated group and control group have the same pre-treatment trend in the outcome of interest after conditioning on observable characteristics. Under this assumption of parallel pre-treatment trends, contemporaneous effects of the policy are differenced out by the change in outcomes of the control group.

6.1.1 Pre-Trend Analysis

Figures 6 and 7 show the trends in health insurance for three cohorts of both females and males respectively. In each figure, the first vertical line indicates April 2010 and the second vertical line indicates September 2010. The cohort of interest is the 19-25 year-olds who were affected by the policy. The main control group, individuals aged 26-29, are included as well as a control group consisting of 16-18 year-olds. I adjust each trend line by subtracting off the average health insurance rate for April 2010. Figures 6 and 7 show that prior to controlling for observable, the 26-29 year-old cohort provides an excellent counterfactual control group for males. However, for females there is a large decrease in health insurance coverage from the 26-29 year-olds from the end of 2008 through 2009. However, the trends are fairly similar from the summer of 2009 up until May of 2010. In addition, the 16-18 year-old have very similar trends as the treated cohort for females, but not males.

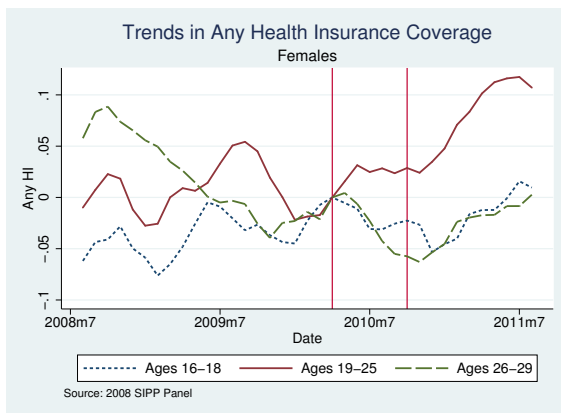


Figure 6: Females

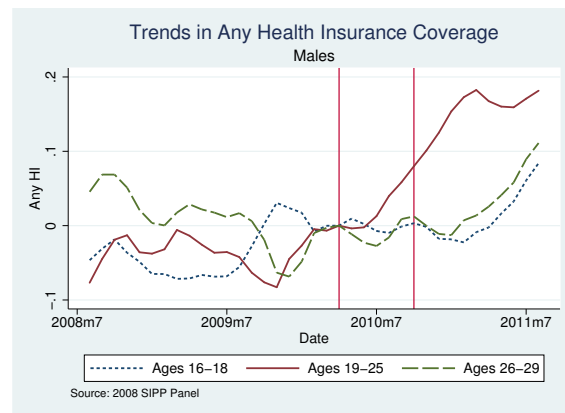


Figure 7: Males

Figures 8 and 9 display the trends in health insurance coverage as a child dependent. As expected, the trend line is mostly flat for the 26-29 year-old cohort as they are not eligible for coverage as child dependents in most states. For both females and males of the treated group the upward sloping trend in dependent coverage suggests that neither control groups may be adequate counterfactuals.

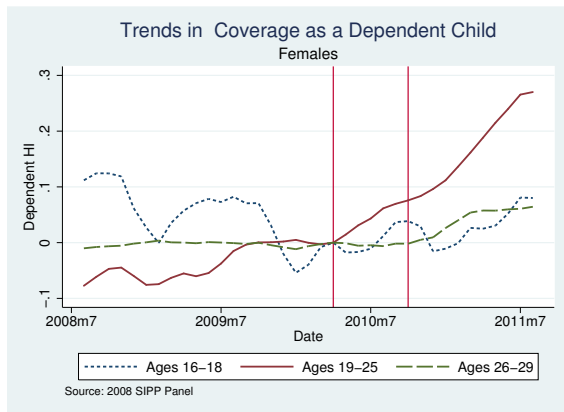


Figure 8: Females

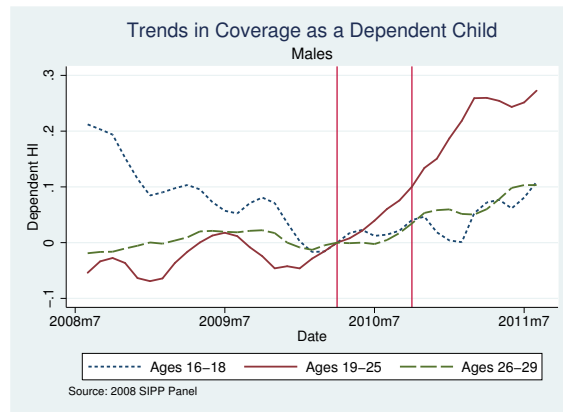


Figure 9: Males

To further analyze the pre-treatment trends I use regression framework to condition out observable characteristics that affect health insurance. I estimate the following equation for the pre-treatment time period:

$$y_{ist} = \alpha_1 eligible_{ist} + \alpha_2 Trend_t + \gamma(eligible_{ist} \times Trend_t) + \theta_s + X_{ist}\beta + \varepsilon_{ist}. \quad (6)$$

y_{iast} is an indicator for health insurance of individual i in state s at time t . $eligible_{iast}$ takes the value of one if the individual is 19 to 25 years old and zero otherwise. law_{st} takes the value of one for observations after the law is implemented, October 2010, and zero prior to May of 2010 (observations from May 2010 through September 2010 are dropped). X_{iast} is a vector of observed controls that includes indicators for marriage, part-time and full-time student status, children, work disability, race and levels of educational attainment. In addition I control for the level and square term of the family income above the poverty level. θ_s is a state fixed effect and ε_{ist} is a vector of unobserved terms. The parameter of interest, γ , indicates whether the treated group and control group had different linear trends from one another.

Table 13: ACA: Pre-Treatment Trend Analysis

	Age 19-25 vs. Age 26-29		Age 19-25 vs. Age 16-18	
	Any Coverage	Dependent Coverage	Any Coverage	Dependent Coverage
Females:				
Trend×Treated	0.0006 (0.0007)	0.0007 (0.0005)	-0.0017** (0.0007)	0.0010 (0.0007)
N	147673	147673	139266	139266
Males:				
Trend×Treated	0.0001 (0.0008)	-0.0003 (0.0005)	-0.0012* (0.0007)	0.0020*** (0.0007)
N	142915	142915	141527	141527

^a Included regressors: Married, Full-time Student, Part-time Student, Children, Work Disability, Race, Poverty Level, Poverty Squared, Education Level FE, and State FE.

^b Standard errors clustered on the individual are presented in parentheses.

^c * 0.10, ** 0.05 and ***0.01 denote significance levels.

Table 13 reports the point estimate of the interaction term in equation 6. The first two columns of results use the 26-29 year-old cohort as the control group and the second two columns of results use the 16-18 year-old cohort as the control group. When using the older cohort as the control group there is no statistical difference in the linear trend between the treated group and the control group. However, the trend is statistically different for both males and females when I use the younger cohort as the control. Therefore, I continue forward only using the 26-29 year-old cohort as the control group.

6.1.2 Difference-in-Difference Framework

To estimate the effect of the ACA on the labor market outcomes of young adults, I use the 2008 SIPP panel of young adults 19-29 years old. I eliminate all observations between May of 2010 through September of 2010 because during these months the policy was not in effect, but many insurance carriers allowed young adults to have access to their parent’s insurance under the new law. The regression I estimate is as follows:

$$y_{iast} = \theta_{sa} + \delta_{st} + \tau(\text{eligible}_{iast} \times \text{law}_{st}) + X_{iast}\beta + \varepsilon_{iast} \quad (7)$$

where y_{iast} is an outcome of interest such as an indicator for the health insurance coverage of individual i with age a in state s at time t . θ_{sa} is a state by age fixed effect and δ_{st} is a state by year fixed effect. $eligible_{iast}$ takes the value of one if the individual is 19 to 25 years old and zero otherwise. law_{st} takes the value of one for observations after the law is implemented, October 2010, and zero prior to May of 2010.¹³ X_{iast} is a vector of observed controls that includes indicators for marriage, part-time and full-time student status, children, work disability, race and levels of educational attainment. In addition, I control for the level and square term of the family income above the poverty level. The estimates from this framework will likely underestimate the true effect because of the intent-to-treat bias. Similar to the estimation framework of the state-policy analysis, I account for serial correlation for an individual across time by clustering the standard errors on the individual.

6.2 Health Insurance Outcomes

The ACA increased the health insurance rate of young adults by a significant margin. The results in Table 14 show that females were approximately 3.2 percentage points more likely to have health insurance and 4.6 percentage points more likely to be covered as a dependent on a parent's plan. Males were approximately 4.7 percentage points more likely to have health insurance coverage and 5.5 percentage points more likely to be covered as a dependent on a parent's plan. These point estimates for females and males are statistically significant at the 1 percent level. The results also show that the increase in health insurance coverage is coming through an increase in private health insurance. This is consistent with the policy because only employer-sponsored insurance is effected. Antwi et al. (2012) found that the ACA increased both the general health insurance rate and dependent coverage rate of young adults. The results in Table 14 provide further support of their findings as the two sets of point estimates are similar.

¹³Observations from May 2010 through September 2010 are dropped.

Table 14: ACA Diff-in-Diff Estimates: Health Insurance Coverage

	<u>Females</u>			<u>Males</u>		
	Any Coverage	Private Coverage	Dependent Coverage	Any Coverage	Private Coverage	Dependent Coverage
DD	0.0317*** (0.0080)	0.0255*** (0.0083)	0.0461*** (0.0061)	0.0468*** (0.0088)	0.0394*** (0.0089)	0.0549*** (0.0063)
Married	0.0352*** (0.0085)	0.0781*** (0.0091)	-0.1029*** (0.0052)	0.1159*** (0.0105)	0.1092*** (0.0106)	-0.0732*** (0.0053)
Full-Time Student	0.0888*** (0.0077)	0.1150*** (0.0083)	0.2240*** (0.0075)	0.1309*** (0.0087)	0.1324*** (0.0089)	0.2470*** (0.0082)
Part-Time Student	0.0430*** (0.0090)	0.0499*** (0.0097)	0.0259*** (0.0078)	0.0631*** (0.0114)	0.0617*** (0.0117)	0.0320*** (0.0094)
Children	0.0511*** (0.0073)	-0.0305*** (0.0077)	0.0296*** (0.0058)	0.0311*** (0.0084)	0.0179** (0.0085)	0.0432*** (0.0063)
Work Disability	0.1483*** (0.0146)	-0.1171*** (0.0149)	0.0120 (0.0114)	0.1890*** (0.0153)	-0.1375*** (0.0137)	0.0311*** (0.0116)
White	0.0112 (0.0089)	0.0807*** (0.0091)	0.0500*** (0.0067)	0.0324*** (0.0098)	0.0699*** (0.0096)	0.0438*** (0.0069)
Poverty Ratio	0.0493*** (0.0023)	0.0853*** (0.0035)	0.0412*** (0.0019)	0.0536*** (0.0024)	0.0673*** (0.0028)	0.0341*** (0.0016)
Poverty Ratio-Sq.	-0.0015*** (0.0001)	-0.0027*** (0.0002)	-0.0010*** (0.0001)	-0.0014*** (0.0001)	-0.0018*** (0.0002)	-0.0008*** (0.0001)
N	216805	216805	216805	211237	211237	211237

^a Included fixed effects for all regressions: Education Level, State-Year and State-Age.

^b Standard errors clustered on the individual are presented in parentheses.

^c * 0.10, ** 0.05 and ***0.01 denote significance levels.

Table 15: ACA Diff-in-Diff Estimates: Employment Outcomes

	LFP	Full-Time Employment	Hours Worked	Employed	# of Jobs	Time Employed
Females:						
DD	-0.0243*** (0.0080)	-0.0198** (0.0086)	-0.6872** (0.3294)	-0.0213** (0.0087)	-0.0250** (0.0114)	-0.0179** (0.0088)
N	204228	204228	204228	204228	204228	204228
Males:						
hline DD	-0.0215*** (0.0064)	-0.0173** (0.0085)	-1.0939*** (0.3477)	-0.0295*** (0.0079)	-0.0379*** (0.0114)	-0.0278*** (0.0081)
N	196157	196157	196157	196157	196157	196157

^a Standard errors clustered on the individual are presented in parentheses.

^b * 0.10, ** 0.05 and ***0.01 denote significance levels.

6.3 Labor Market Outcomes

This large effect on dependent coverage suggests a strong first stage that will potentially result in individuals altering their labor supply. Estimates of equation 7 on labor force participation, full-time employment, usual hours worked per week, current employment status, number of jobs held this month, and the proportion of time this month one was employed are reported in Table 15. Similar to the labor market outcomes from the state policies, both males and females reduced their labor supply as a result of the ACA. The ACA reduced the labor force participation by 2.4 percentage points and 2.2 percentage points for females and males respectively. This decrease in labor supply is robust across all the of the labor market outcomes presented. Unlike the state policies that suggested that females were more affected than males, the employment outcomes from the ACA are very similar across gender.

6.4 Education and Marriage Outcomes

Table 16 reports the DD estimates for estimating equation 7 in which the outcome variables are indicators full-time student, part-time student, married, and cohabitate. Similar to the state policies, I find the ACA caused an increase in the probability of being a full-time student for treated females. However, under the ACA, I find a similar effect for males. For both females and males the point estimate is statistically significant at the 10 percent level and suggests a 1.8 percentage

Table 16: ACA Diff-in-Diff Estimates: Student and Marriage

	Full-Time Student	Part-Time Student	Married	Cohabitate
Females:				
DD	0.0185* (0.0110)	-0.0017 (0.0085)	-0.0257*** (0.0088)	-0.0052 (0.0057)
N	136181	136181	216805	216805
Males:				
DD	0.0180* (0.0103)	0.0009 (0.0069)	-0.0016 (0.0082)	0.0021 (0.0057)
N	128456	128456	211237	211237

^a Included fixed effects for all regressions: Education Level, State-Year and State-Age.

^b Standard errors clustered on the individual are presented in parentheses.

^c * 0.10, ** 0.05 and ***0.01 denote significance levels.

point increase in the likelihood of being a full-time student. Similar to the state policy analysis, I find no effect on part-time student status.

As suggested earlier, the state policy analysis did not provide a robust identification environment to test the impact of the state policies on marriage rates because most states required individuals to be single. Under the ACA both single and married individuals under the age of 26 could gain access to their parents health insurance. Using the DD estimation strategy with the ACA, I find that females under the age of 26 are now 2.6 percentage points less likely to be married. This result is consistent with the idea that the marginal benefit of marriage decreases when one is able to gain health insurance through another source. It is not surprising that the effect is only significant for females. The demand of health insurance is greater for females than males and in marital decisions it is more common for females to be secondary earners and thus rely on their husband for health insurance.

7 Discussion and Conclusion

With the prior literature on health insurance and the labor market focussed on the joint decision making in the household, retirees and Medicaid expansion, little is known about the young adult population. This paper not only contributes to understanding the policy implications of expanding dependent health insurance, it also shows the importance of health insurance in the decisions of young adults. The results suggest that expanding dependent health insurance coverage decreased the labor supply of eligible young adults who were now able to obtain coverage under a parent's plan. The analysis of the state policies found the expansion of dependent coverage resulted in a 4.6 percentage point decrease in female labor force participation and a 1.7 percentage point decrease in male labor force participation. In addition to labor force participation, the results show decreases in a number of labor market outcomes for both males and females. During the state policies females had a labor force participation of approximately 0.75, therefore, a federal policy that granted insurance to this group of young adults would decrease the labor force participation of this cohort by approximately 6 percent. These outcomes suggest that large health care reform will result in large changes in the labor market.

The results from the ACA suggest that both males and females have significant increases in the health insurance rate as result of the federal policy. Prior to the ACA, females had an uninsurance rate of 0.29 and males had an uninsurance rate of 0.39. The point estimates at the individual level from the health insurance outcomes suggest that the ACA increased the health insurance rate by 3.2 percentage points for females and by 4.7 percentage points for males. This is equivalent to an 11 percent and 12 percent decrease in the uninsurance rate for females and males, respectively. In similar fashion, the ACA increased the rate of dependent coverage by 16 percent and 21 percent for females and males, respectively. Given the relatively larger impact of the ACA on dependent coverage, the ACA had a large reallocation effect on health insurance. For the employment and student outcomes the results from the ACA are qualitatively similar to the findings from the state policies. At the individual level, the ACA decreased labor force participation by 2.4 percentage point for females and by 2.2 percentage point for males.

The results from the state policies suggests that the expansion of dependent coverage increased

the likelihood of being a full-time student by 3.2 percentage points for females. However, the result for males indicated an increase by 2.1 percentage points but was not statistically significant at a reasonable level. The sizable increase in full-time student status as a result of the policy suggests there could be potential welfare gains for expanding dependent health coverage. Although the analysis of the state policies revealed no evidence that marriage rates were affected by dependent coverage laws, the identification environment did not provide the power to test the result. Under the ACA, females are 2.6 percentage points less likely to be married. However, I found no effect for males.

While this paper highlights important policy implications of expanding dependent health insurance coverage, there is much left on the table in regards to understanding the welfare implications. Future work should consider additional outcomes, such as wage effects and/or the labor market outcomes of parents, that affect the welfare implications of the policy. In addition, this paper could be improved by the use of longitudinal data that spans more than four years. Specifically, if one is able to accurately follow both an individual and their parent then one can avoid the intent to treat framework as applied in this paper. However, the results from the state-policy and ACA analysis provide robust evidence that expanding dependent coverage decreases the labor supply and alters the lifestyle choices of young adults.

8 Additional Figures and Tables

Figure 10: State Policies to Expand Dependent Coverage in 2001

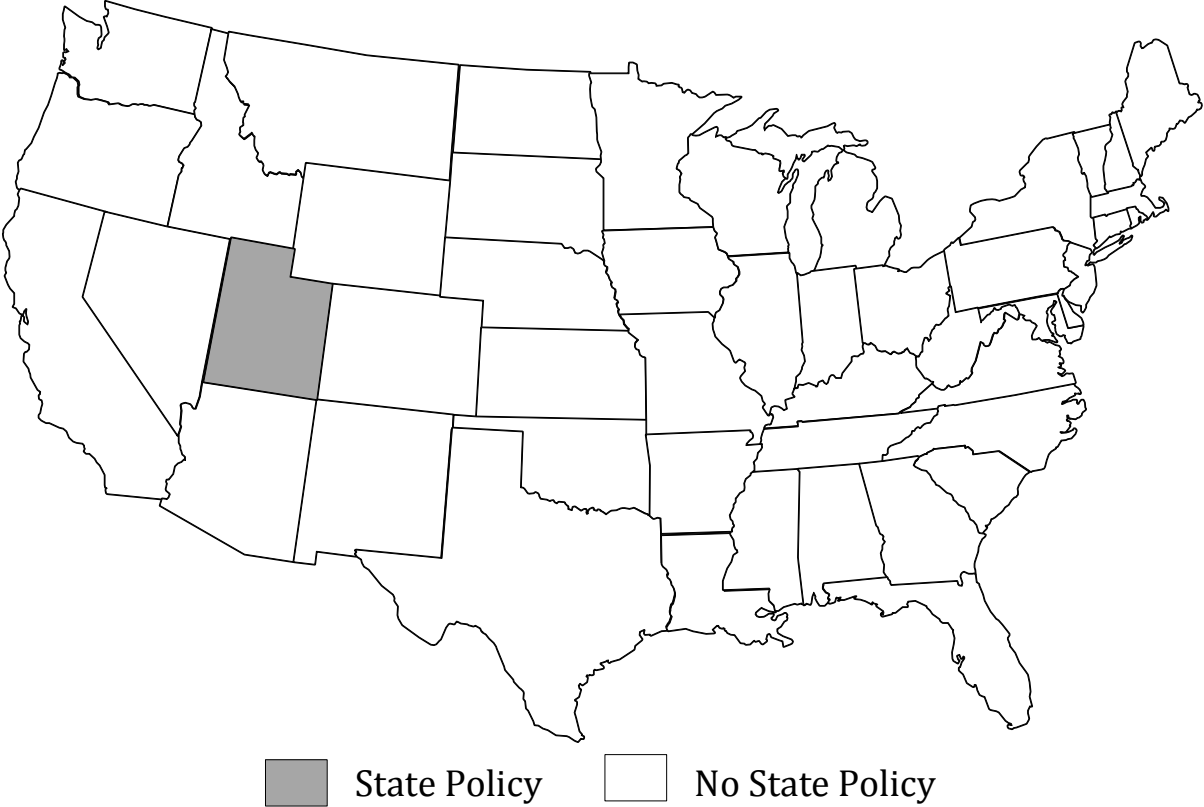


Figure 11: State Policies to Expand Dependent Coverage in 2010

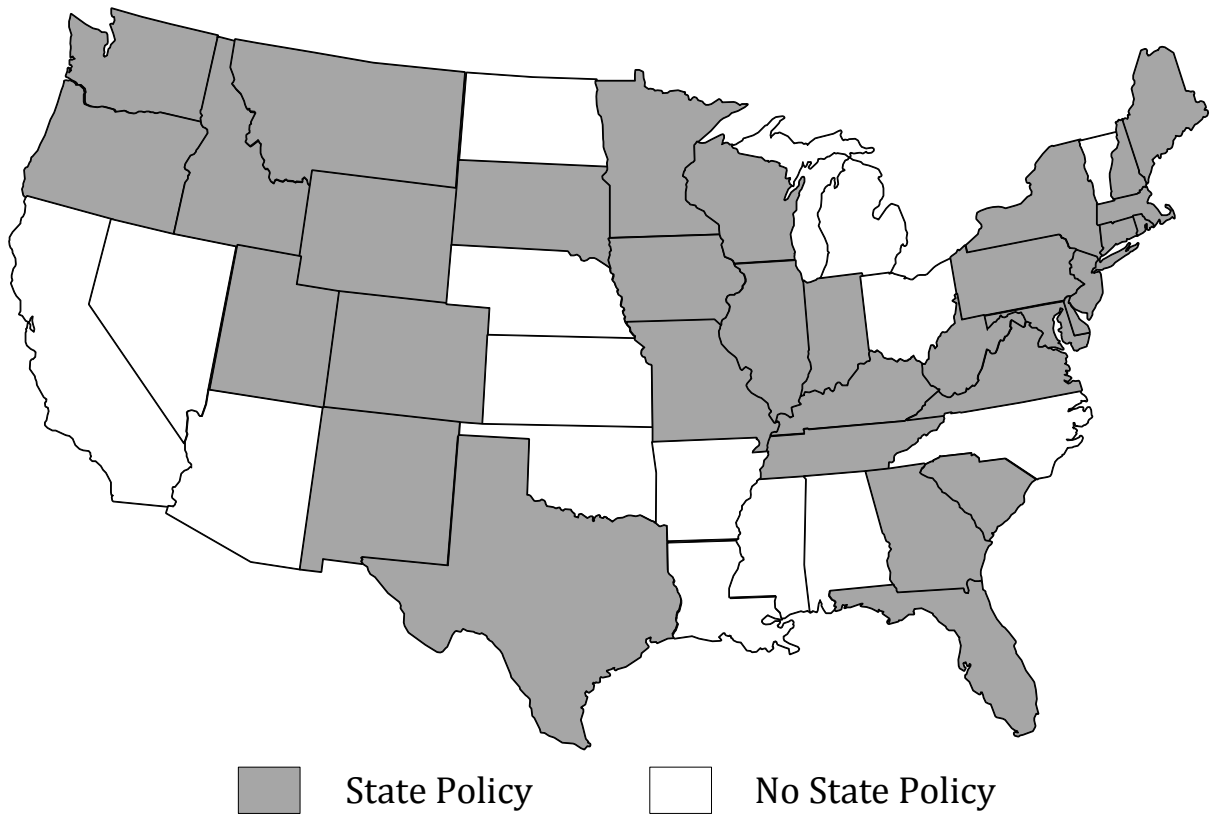


Table 17: State Policy Diff-in-Diff Estimates: Health Insurance Coverage

	<u>Females</u>			<u>Males</u>		
	Any Coverage	Private Coverage	Dependent Coverage	Any Coverage	Private Coverage	Dependent Coverage
DD	0.0014 (0.0073)	0.0026 (0.0077)	0.0118** (0.0058)	-0.0072 (0.0080)	-0.0043 (0.0081)	0.0095* (0.0057)
Married	0.0359*** (0.0053)	0.0849*** (0.0058)	-0.0890*** (0.0035)	0.1116*** (0.0066)	0.1155*** (0.0066)	-0.0635*** (0.0037)
Full-Time Student	0.0795*** (0.0052)	0.1101*** (0.0056)	0.2254*** (0.0051)	0.1272*** (0.0059)	0.1223*** (0.0062)	0.2568*** (0.0056)
Part-Time Student	0.0318*** (0.0060)	0.0407*** (0.0066)	0.0064 (0.0049)	0.0658*** (0.0076)	0.0620*** (0.0078)	0.0451*** (0.0064)
Children	0.0624*** (0.0047)	-0.0064 (0.0050)	0.0375*** (0.0038)	0.0389*** (0.0054)	0.0259*** (0.0054)	0.0474*** (0.0042)
Work Disability	0.1280*** (0.0089)	-0.1464*** (0.0097)	0.0145** (0.0072)	0.1468*** (0.0109)	-0.1548*** (0.0112)	0.0276*** (0.0078)
White	-0.0142*** (0.0055)	0.0674*** (0.0062)	0.0366*** (0.0046)	0.0312*** (0.0067)	0.0582*** (0.0068)	0.0261*** (0.0048)
Poverty Ratio	0.0432*** (0.0018)	0.0744*** (0.0030)	0.0337*** (0.0016)	0.0466*** (0.0019)	0.0567*** (0.0024)	0.0256*** (0.0010)
Poverty Ratio-Sq.	-0.0011*** (0.0001)	-0.0020*** (0.0002)	-0.0007*** (0.0001)	-0.0010*** (0.0001)	-0.0013*** (0.0001)	-0.0005*** (0.0000)
N	594548	594548	594548	563936	563936	563936

^a Included fixed effects for all regressions: Education Level, State-Age and Year-Age.

^b Standard errors clustered on the individual are presented in parentheses.

^c * 0.10, ** 0.05 and ***0.01 denote significance levels.

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A Appendix: Measurement Error

For an individual to be treated by the policy they must 1) meet the eligibility requirements, and 2) have a parent with employer sponsored health insurance. However, I only observe whether the eligibility criteria of the individual is satisfied. Therefore, I have measurement error in the assignment of treatment. Specifically, I assign treatment to individuals who are not actually affected by the policy. The affect of the measurement error is not straightforward because the error is always in one direction. Below I show that the affect of the measurement error simply will result in attenuation bias of the point estimate of interest. Interestingly, the proof shows that this type of measurement error is simply the same error that results in the setting of classical measurement error.

Let x_i^* take the value of 1 if an individual is treated (satisfies the eligibility criteria and also has a parent with employer sponsored insurance), and zero if the individual is not treated. Therefore, the equation of interest is,

$$y_i = x_i^* \beta + \varepsilon_i$$

However, x_i^* is not observed. The assigned treatment is defined as x_i which takes the value of 1 if an individual meets the eligibility criteria and zero otherwise. Therefore, treatment is overly assigned. Specifically, the $Pr(x^* = 1) < Pr(x = 1)$ and $x = 0 \Rightarrow x^* = 0$. Given that treatment is overly assigned it follows that the relationship between x_i and x_i^* is

$$x_i = x_i^* + \nu_i.$$

ν_i takes the value of zero if treatment is accurately assigned (an individual both satisfies the eligibility criteria and has a parent with employer sponsored insurance), and the value of 1 if treatment is not accurately assigned (an individual only satisfies the eligibility criteria). Therefore, the probability distribution of ν is

$$\begin{aligned} Pr(\nu = 1) &= Pr(x = 1)(1 - Pr(x^* = 1)), \\ Pr(\nu = 0) &= Pr(x = 1)Pr(x^* = 1) + P(x = 0). \end{aligned}$$

The OLS estimate of y on x is

$$\hat{\beta} = \frac{\sum(x_i^* + \nu)(x_i^* \beta + \mu_i)}{\sum(x_i^* + \nu)^2}$$

Under the assumptions that $E[x^* \varepsilon] = 0$ and $E[\nu \varepsilon] = 0$ it follows that

$$plim \hat{\beta} = \beta \frac{E[x^{*2}] + E[x^* \nu]}{E[x^{*2}] + 2E[x^* \nu] + E[\nu^2]}. \quad (8)$$

However, by construction of the assigned treatment,

$$E[x^* \nu] = 0.$$

This is derived from the fact that both x^* and ν are Bernoulli random variables and that $x^* = 1 \Rightarrow \nu = 0$ and $\nu = 1 \Rightarrow x^* = 0$. It follows that equation 8 simplifies to

$$plim \hat{\beta} = \beta \frac{E[x^{*2}]}{E[x^{*2}] + E[\nu^2]}$$

Therefore, the measurement error causes attenuation bias in the estimated β . Moreover, this result is similar to the case of classical measurement error that further assumes the error component is mean zero with finite variance.