ESSAYS ON HEALTH COVERAGE EXPANSIONS AND ITS IMPACTS ON LOW INCOME POPULATIONS

A DISSERTATION SUBMITTED TO THE GRADUATE DIVISION OF THE UNIVERSITY OF HAWAIʻI AT MĀNOA IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

IN

ECONOMICS

May 2023

By

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Acknowledgements

I would like to recognize everyone who have made this dissertation possible.

First, I recognize my committee chair, Timothy Halliday, whose wisdom, guidance, and mentorship inspired me to follow in his footsteps as a health economist. I will never forget the countless hours we spent brainstorming ideas and sharing our passion for research. His unwavering support and belief in my abilities gave me the confidence to recognize my potential as a skilled economist. I have the utmost respect and admiration for him, and I will always treasure the lessons he taught me.

I am thankful for my committee member Victoria Fan, who allowed me to work in her lab as a research assistant for three years. The skills and knowledge I gained under her were invaluable. She not only taught me how to become a better researcher but also encouraged me to believe in myself and my abilities.

I am very grateful for my committee member Sang-Hyop Lee, whose class provided me with the programming skills that are showcased in this dissertation. I will always cherish the talks we had and how he supported me in my times of hardship. I thank my committee member Teresa Molina for her invaluable advice and guidance during my third year. Her contributions were instrumental in advancing my research and have taught me much. I also thank my committee member Ruben Juarez, who played a pivotal role in my decision to pursue a PhD at the university. I am honored to have him as my sponsor for graduation.

Thank you to all of my amazing friends, whose love, support, and faith have been a constant source of inspiration throughout my journey. Your encouragement and unwavering belief in me have helped me to overcome obstacles and achieve my goals, and I am forever grateful for the memories and experiences we've shared together. The friendships I have built with you will last forever.

Thank you to my classmates Mel Lorenzo Accad, Thuy Doan, Hazel Hotchandani, Sarah Medoff, Krit Phankitnirundorn, Ivan Rivadeneyra, and Deepti Sikri for the bond we shared together in our first year and beyond. I am proud to have been a part of your class.

I extend my deepest appreciation to my family, who have been my constant source of support and encouragement throughout the doctoral journey. Thank you mom for your unconditional love, unwavering support, and sacrifices that have made me the person I am today. Your strength and resilience have been a constant source of inspiration, and I am proud to call you my mom. I am also grateful for my dad, and my brothers and sisters. I love you all dearly.

Words cannot express how thankful I am for my girlfriend Maile Ishikawa. You are my soulmate, my best friend, and my future wife. Your love has given me the strength and courage to face the challenging adversities of pursuing a PhD. This is only the first step towards pursuing a long and fulfilling life with you. I love so dearly and with every fiber of my being. I am also grateful my cat Jules for being the best daughter I could ever ask for. Daddy loves you very much.

Lastly, I dedicate this dissertation to my grandmother Carol Ann Fortier, who was my greatest supporter and inspired me to become the scholar I am today. Even though you are gone, I feel your presence every day, giving me the strength to overcome any challenge I encounter. I wish you were here with me, but I know that you are looking down on me from above, cheering me on. Thank you for believing in me and for giving me so much purpose. I love you forever and you will always be in my heart.

Introduction

Medicaid has long been considered a significant safety net program for health coverage for low-income individuals and children in the United States. The 2010 Affordable Care Act (ACA) increased Medicaid eligibility for millions of low-income Americans in order to improve health care access and outcomes. However, while the vast majority of states have agreed to this expansion, a few have refused. Consequently, there is now a significant disparity in health care outcomes and access between states that participated in the expansion and those that did not, trapping millions of people in a "coverage gap" where they have no access to affordable health coverage. Recent reports of prospective cuts or damaging provisions to Medicaid and the Children's Health Insurance Program (CHIP) have alarmed healthcare groups and the general public. A variety of factors have influenced the proposed Medicaid and CHIP cuts and requirements, including economic constraints, ideological hostility to government-funded healthcare, and unfavorable biases held against Medicaid enrollees. The proposed cuts could result in reduced eligibility, decreased coverage, and increased costs for beneficiaries, further exacerbating the "coverage gap" that is disproportionately borne by racial and ethnic minorities.

This dissertation seeks to evaluate the effectiveness of the ACA Medicaid expansion on covering vulnerable populations under Medicaid and CHIP. Specifically, it aims to answer the following research questions: Who did the ACA Medicaid expansion really impact, and do these individuals conform to the beliefs surrounding them? To answer these questions, I draw upon techniques from econometrics and economic theory to conduct a comprehensive analysis of health coverage outcomes in both expansion and non-expansion states. This dissertation utilizes publicly available data from the American Community Survey, the Kaiser Family Foundation, Medicaid.gov and the Bureau of Labor and Statistics for its empirical analyses.

The dissertation is structured as follows. Chapter 1 focuses on low-income childless adults and estimates the probability of being a complier (i.e., those induced by the expansion to seek Medicaid) from the ACA Medicaid expansion. This study aims to not only identify those directly impacted by the expansion, but also validate whether the stigmatization held against them is true. Chapter 2 focuses on children, a population that was not an intentional target group of the ACA Medicaid expansion, and examines if the expansion led to any increases in Medicaid coverage for those who were already eligible prior to the expansion, i.e., the “welcome mat” effect. This study aims to assess the impacts of the ACA Medicaid expansion on a population that, in theory, should not have been affected.

Overall, this dissertation contributes to our understanding of how effective the ACA Medicaid expansion was in covering many vulnerable demographics. These findings have significant implications for both policymakers and academics, and provide important insights to consider when discussing the future of Medicaid and CHIP.

Abstract

This dissertation is composed of two chapters that apply econometric techniques to evaluate the impacts of the Affordable Care Act Medicaid expansion on health coverage for low-income populations. The first chapter evaluates who enrolled in Medicaid as a consequence of the Affordable Care Act (ACA). Using the 2010–2017 American Community Survey, I estimate how characteristics relating to work status and race/ethnicity affect the probability that an individual will be a complier, defined as those induced by the ACA Medicaid expansion to obtain Medicaid coverage. Across all states, I find that part-time workers, not non-workers, are the most likely to be compliers. This finding is not consistent with certain notions that Medicaid participants are the "undeserving poor" - a sentiment that may have hindered efforts to expand Medicaid in certain states. Additionally, I find that in non-expansion states, many of which have high Black populations, the probability of being a complier is higher for Blacks than for other racial/ethnic groups, suggesting that Black people in non-expansion states would be the largest beneficiaries of any new expansions. This paper not only identifies the types of individuals who were already impacted by the expansion but also identifies which populations would benefit the most from subsequent expansions.

The second chapter analyzes how effective was the ACA in enrolling children already eligible for Medicaid and Children Health Insurance Program (CHIP). Utilizing the American Community Survey (ACS) from 2012 to 2017, I adopt a difference-in-differences approach that measures the changes in public and private coverage for Medicaid and CHIP eligible children before and after the enactment of the ACA Medicaid expansion. I find that there are modest yet significant increases in public coverage for children who were previously eligible for Medicaid and CHIP prior to the expansion, providing evidence of a "welcome mat" effect. However, I observe significant crowding out in employer-sponsored insurance for both previously eligible children and children who became newly eligible as a result of the new adjusted gross income (MAGI) thresholds established after 2014. My findings not

only establish, under the ACA Medicaid expansion, clear evidence of a “welcome mat” effect for children across various age and income groups, but they may also suggest that parents favor fully subsidized public coverage over partially subsidized private insurance for their children.

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Chapter 1

Who Did the ACA Medicaid Expansion Impact? Estimating the Probability of Being a Complier

1.1 Introduction

There has been a wide body of literature documenting the effectiveness of the Affordable Care Act (ACA) in providing health coverage for low-income adults. One of its key components, the 2014 Medicaid expansion, has led to significant and greater reductions in the rates of the uninsured for low-income adults residing in states that expanded Medicaid, relative to states that did not elect to do so (Courtemanche et al., 2017; Decker et al., 2017; Kaestner et al., 2017; Miller and Wherry, 2017; Simon et al., 2017; Sommers et al., 2015; Wherry and Miller, 2016).

Before the Affordable Care Act (ACA), disparities in health coverage across racial/ethnic groups and socioeconomic status had been widely recognized in the literature (Courtemanche et al., 2016; Courtemanche et al., 2017; Courtemanche et al., 2019; Lee and Porell, 2020). Key provisions of the ACA, such as Medicaid expansion, subsidized Marketplace coverage, and the individual mandate, were developed for the purpose of alleviating the disparities that are attributed to race/ethnicity. Although the ACA reduced these disparities, they have yet to be eliminated. This has prompted researchers to examine how the ACA Medicaid expansion disproportionately affected people of all races, ethnicities, and socioeconomic backgrounds.[1] However, these studies do not provide direct estimates of the composition of the compliers, or estimate the likelihood of any given individual being a complier. The compliers in this paper refer to the individuals who were induced by the ACA Medicaid expansion to enroll in Medicaid.

In this paper, I employ techniques from econometrics to identify which types of individuals, measured on a set of observables, are most likely to be compliers. First, I adopt methods from previous studies to identify the characteristics of the compliers (Abadie, 2002; Abadie, 2003; Abrigo et al., 2021 ; Imbens and Rubin, 1997; Katz et al., 2001; Kowalski, 2016). Then, I estimate a saturated probit model and utilize methods from Abadie (2003) to derive the probability of being a complier by race and ethnicity and work status. I also estimate the likelihood of being either an "always taker," or someone who had already enrolled in Medicaid prior to the expansion, or a "never taker," or someone who had never enrolled even if a state chose to expand Medicaid.

My identification strategy involves several estimation techniques. First, I exploit the design of the 2014 ACA Medicaid expansion and adopt a difference-in-differences (DID) strategy to estimate the impacts of the expansion on Medicaid enrollment for low-income childless adults. Using data from the American Community Survey (ACS) from 2010 to 2017, I find that the expansion increased Medicaid coverage by 15.7 percentage points for low-income childless adults. This result is slightly higher than those reported in previous studies, ranging between 2 and 15 percentage points (Courtemanche et al., 2017; Duggan et al., 2019; Frean et al., 2017; Leung and Mas, 2018; Simon et al., 2017; Wherry and Miller, 2016). However, larger impacts have been associated with studies with longer post-expansion time periods (Courtemanche et al., 2017; Courtemanche et al., 2019) and where their analysis is restricted to low-income childless adults Simon et al. (2017).[2]

Next, I compute the average characteristics of the compliers, always takers, and never takers using the methods outlined in Abrigo et al. (2021) and Kowalski (2016). The compliers in this natural experiment are disproportionately made up of Black individuals and those in the middle of the distribution for work status. The always takers and never takers are largely from the lower and upper ends of the distributions for work status, respectively. This finding is similar to what was found by Abrigo et al. (2021) in their evaluation of health insurance expansion for elderly citizens in the Philippines.

[1]See Medicaid and CHIP Payment and Access Commission (MACPAC) (2021) for a more comprehensive review of the literature.

[2]Majority of studies limited their sample period to 2015 and did not restrict their analysis to lower income samples or childless adults.

I estimate a saturated probit model that interacts my demographic variables of interest with my treatment assignment variable, i.e., an indicator for the state's expansion status in a given year. Then, I use these estimates with methods from Abadie (2003) to estimate the probability of being a complier, a never taker, and an always taker, conditional on either work status or race/ethnicity. Overall, the probability of being a complier was greater in expansion states when compared to non-expansion states. When broken down by work status, part-time workers had the highest likelihood of being a complier across all work groups and states. Evaluating by race/ethnicity, I discovered that Black individuals were more likely to be compliers in non-expansion states than other racial/ethnic groups, many of which had large Black populations, implying that Black people in non-expansion states would benefit most from any future expansions. However, in states with large Black populations that had expanded Medicaid, White people were more likely than Black people to be compliers.

My findings are relevant to the implementation of the Section 1115 Medicaid waivers, which require that users satisfy certain work requirements in order to be eligible for continuous Medicaid coverage.[3] These waivers were created on the premise that Medicaid is a safety net program for the "undeserving poor". While low-income individuals who are either children, pregnant women, elderly, or those with disabilities make up a group largely considered to be the "deserving poor," the "undeserving poor" have been labeled as able-bodied adults who are unable to become self-sufficient and must be incentivized to work (Applebaum, 2001; Gans, 1995; Moffitt, 2015). My findings demonstrate that the characteristics that define the "undeserving poor" do not align with those that define the compliers in the ACA Medicaid expansion, given that across all states, part-time workers were the most likely work group to be compliers.

My findings suggest that, compared to other racial/ethnic groups, Black childless adults would be the highest beneficiaries in the majority of states that haven't expanded Medicaid. This is important given that out of the top 13 states (including DC) that account for 48% of the Black population, only five states have elected to expand Medicaid between 2014 and 2017 (Buettgens and Kenney, 2016). Additionally, I estimate that the beneficiaries of the expansion in these states were primarily White individuals rather than Black individuals. As a result, my findings have important implications for reducing coverage disparities for Blacks, who are disproportionately residing in non-expansion states.

A small number of studies have integrated complier analysis into the context of policy evaluations for health insurance programs (Abrigo et al., 2021; Ko et al., 2020; Kowalski,

[3]For a list of approved and pending Section 1115 waivers by state, see Kaiser Family Foundation (2022a).

2016). None of these studies, however, estimated complier probabilities. This paper advances the literature by being the first to estimate how individual characteristics such as work status and race/ethnicity determine the probability of being a complier in a health policy setting. Concerning the Medicaid expansion, this study serves to provide the impacts of the policy at the state level, a contribution that has been absent in the literature. Finally, to the best of my knowledge, this is the only study to provide direct estimates of the compliers, always takers, and never takers of the ACA Medicaid expansion.

Subsequent sections of this study proceed as follows. Section 1.2 provides a brief overview of the ACA Medicaid expansion. Sections 1.3 and 1.4 discuss the data and empirical design used in this study. Section 1.5 presents the results on the impact of the ACA Medicaid expansion on low-income childless adults, the characteristics of the compliers, and the conditional probabilities of the compliers, never takers, and always takers. Finally, Section 1.6 discusses the policy implications and concludes.

1.2 Background

The Affordable Care Act (ACA) delivered the most significant changes in the history of the United States' health care system since Medicare and Medicaid were first implemented in 1965. Specifically, the expansion of Medicaid to all people with earnings below 138 percent of the federal poverty line (FPL) was one of the key components introduced in the ACA.[4] In 2012, the Supreme Court ruled that states could voluntarily elect to participate in the expansion instead of being subjected to the mandate. As a result, on January 1st, 2014, twenty-five states (including DC) enacted the Medicaid expansion, with seven additional states following between 2014 and 2017.[5] As of January 1st, 2023, 12 states have opted out of participating in the expansion, resulting in limited Medicaid eligibility for low-income childless adults residing in these states.

Prior to the enactment of the ACA, the majority of state Medicaid programs did not cover low-income childless adults unless they were disabled or chronically ill. Those receiving federal assistance through supplemental security income (SSI) automatically qualify for Medicaid. Some states provided government assistance to this population with state-only

[4]The statutory cutoff for Medicaid eligibility in expansion states is 133% of the FPL, but the ACA requires states to apply a standard income disregard equivalent to 5% of the FPL, essentially raising the eligibility threshold to 138% of the FPL.

[5]Figure A.1 in the appendix maps each state's expansion status from 2014-2017.

dollars or through special Medicaid waivers.[6] However, beginning April 1, 2010, states were able to provide coverage for this population without a special waiver through Medicaid state plans with regular federal matching payments. Under these programs, a small portion of childless adults were covered under Medicaid prior to the expansion.

Another component of the ACA was the introduction of tax credits for private insurance purchased through Marketplace exchanges. Individuals who were ineligible for Medicaid qualified for income-based tax credits if their income was between 100-400% of the FPL.[7] Given that not every state participated in the expansion and the premium subsidies in these states are limited to those with incomes between 100-400% of the FPL, this leaves nearly 2.2 million adults in a "coverage gap" with incomes too high to qualify for Medicaid, but below the minimum threshold necessary to become eligible for subsidies for Marketplace coverage (Garfield et al., 2021). The coverage gap is borne heavily by Black individuals given that they disproportionately reside in non-expansion states. Therefore, coverage options are disproportionately limited for this demographic, thus allowing the disparities in health coverage by race/ethnicity to remain.

The ACA redefined how financial eligibility is determined in Medicaid for non-disabled groups with the introduction of the Modified Adjusted Gross Income (MAGI) system. The MAGI is calculated by applying various deductions to adjusted gross income (AGI). The ACA required states to convert their eligibility criteria prior to its enactment to MAGI-equivalent levels. This eliminated the use of income disregards and deductions other than the standard income disregard, which equates to 5% of the FPL. Other non-income-based features of the ACA improved eligibility determination for Medicaid. This included reductions or eliminations of waiting periods; real-time eligibility determination; implementation of outreach and enrollment strategies; and shifting to modernized, technology-driven approaches for enrollment and renewal procedures.

Under the elective Medicaid expansion, increases in eligibility were observed primarily for childless adults, as they were excluded from most programs that previously expanded Medicaid to other populations. Several states (CA, CT, DC, MN, NJ, and WA) had limited or full expansions to parents prior to the ACA Medicaid Expansion phased in 2014.[8] The

[6] See Somers et al. (2010) for list of state programs that covered low-income childless adults in Medicaid prior to the expansion.

[7] The size of these tax credits amount between 2% to 9.5% of income on a sliding scale basis. These credits represent the maximum share of income that an individual pays for private coverage at the silver plan level (70% of a plan's actuarial value).

[8] See (Sommers et al., 2013) for further information on timing and details.

mean eligibility threshold rates for children were very generous and relatively robust before and after 2014. Prior to the ACA expansion, the mean eligibility threshold for non-disabled childless adults was roughly 30% of the FPL in expansion states.[9] After the expansion, the mean threshold increased to 138% of the FPL in expansion states, including states that later expanded. The mean Medicaid eligibility threshold rates in non-expansion states, however, remained at 0% of the FPL both before and after the expansion.[10] Figure A.2 in the appendix summarizes the changes in the mean Medicaid eligibility thresholds by state between 2013 and 2014.

1.3 Data

1.3.1 American Community Survey

I utilize the American Community Survey (ACS) as the main data source for my analysis. The ACS is conducted annually by the United States Census Bureau and is the largest household survey in the country. The survey samples approximately 3 million individuals each year, representing over 92% of the population in the United States. If selected, respondents are required by law to answer all questions in the survey as accurately as possible. This reduces the likelihood of issues arising from sample selection. The ACS includes information on health insurance coverage, measures of poverty and income, individual demographics, employment, and geographic location. I restricted my sample to the years 2010–2017, providing four years of data before the ACA and four years after it was introduced. The ACS identifies all 50 states (including DC) along with 2300 localities, or Public Use Microdata Areas (PUMAs). I conduct my analysis at the individual-state level.

The ACS includes ratios of family income to poverty thresholds for households. Income is measured as family income before taxes. Measures not considered when calculating family income include non-cash benefits, capital gains or losses, and tax credits. The poverty lines are calculated based on family size and the number of related children under 18 years of age. These thresholds vary across years and are directly from the Current Population Survey (CPS).[11] Poverty status is calculated as a ratio of family income to the poverty threshold set

[9]Several states partially (AZ, CO, CT, DE, HI, MN, and NY) or fully (DC, VT) expanded Medicaid to childless adults prior to 2014.

[10]The only exception was Wisconsin, which elected to increase state-level eligibility for childless adults to 100% of the FPL starting in 2014.

[11]The Census is unable to determine poverty status for people in military barracks, college dormitories,

for that individual. For example, in 2015, the poverty threshold for a three-person family with one child under 18 was $19,708. If a family's income for that year was $40,000, their poverty status would be approximately 2.03 or 203% above the FPL.

I utilize the following health insurance variables from the ACS: Medicaid, employer sponsored insurance (ESI), non-group private insurance, and no health insurance (uninsured). Collectively, these categories comprised nearly 97% of non-elderly childless adults in my sample, with the remainder insured by Medicare or VA. The ACS is generally a reliable source used by the Census in assessing health insurance coverage for the U.S. population. However, ACS is limited in assessing Medicaid status in that it measures Medicaid status by asking if a respondent merely received "Medicaid, Medical Assistance, or any type of government assistance plan for low-income individuals or individuals with disabilities". This potentially serves as a caveat in my study, as respondents may misreport private coverage as public coverage and vice versa.[12]

The Supreme Court's 2012 ruling on Medicaid expansion created a quasi-experimental setting that allowed me to assign states into treatment and control groups based on their decision and timing to expand Medicaid. States are assigned to the treatment group if they expand Medicaid to 138% of the FPL in a given year and to the control group if not. Therefore, the number of states in the treatment and control groups varies across years, as seven states elected to expand Medicaid between 2014-2017. Data on both states' expansion status and Medicaid eligibility thresholds is taken directly from the Kaiser Family Foundation (Kaiser Family Foundation 2022b). I excluded states that fully expanded Medicaid prior to 2014 (DC and VT) due to eligibility thresholds for these states being higher than 138% of the FPL. Additionally, I excluded Wisconsin from my sample as they did not participate in expansion, but increased eligibility for childless adults to 100% of the FPL in 2014.[13]

I restricted my sample to individuals that met the following criteria: aged between 26 and 64, childless, non-disabled, and with incomes below 138% of the FPL. I imposed these restrictions to control for alternative pathways into Medicaid that disregard state by year income eligibility thresholds. Individuals aged 65 and over qualify for Medicare. The ACA allowed individuals under 26 years old to remain on their parents' health insurance under the dependent coverage mandate. Additionally, the eligibility thresholds are more

institutional group quarters, or in living situations without conventional housing.

[12] Mach and O'Hara (2011) found that the ACS typically overestimates non-group private coverage compared to other data sources.

[13] As a robustness check, I run my analysis without excluding these states. The results do not differ significantly from what is reported in the main result.

generous for children and parents compared to childless adults. Regarding disability status, there are alternative pathways for individuals with disabilities that exist outside of income determination. Lastly, I restricted my sample to those with incomes less than 138% of the FPL to partial out the effects of crowd-out of non-group private insurance in the Marketplace. It is important to note that limiting my sample to a small income group introduces potential issues regarding measurement error. First, family incomes in the ACS are self-reported and may not accurately depict what is used to determine eligibility for Medicaid. Moreover, since eligibility is determined based on MAGI, income may be higher than what is reported for an individual. As a result, these elements serve as potential constraints in my design.

1.3.2 Summary Statistics

Table 1.1 displays the summary statistics of the individual demographics by state expansion status. The before and after periods in expansion states are determined by when each state expanded Medicaid, whereas the before and after periods in non-expansion states are determined by the years 2010–2013 and 2014–2017, respectively. Overall, there are no notable differences across time periods in either group. However, comparing states' expansion status, non-expansion states had a higher Black population and a greater portion of those who are less educated, working full-time, and with higher incomes.

Table 1.1: Summary Statistics of Control Variables by States' Expansion Status (0-138% FPL)

	Expansion States				Non-Expansion States			
	Before		After		Before		After	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Main Demographics								
Female	0.48	(0.50)	0.50	(0.50)	0.49	(0.50)	0.51	(0.50)
Age (years)	45.86	(11.82)	46.17	(12.22)	46.18	(11.61)	46.57	(11.99)
Income (% of FPL)	68.32	(45.87)	66.98	(45.94)	71.27	(45.10)	70.45	(45.75)
Married	0.23	(0.42)	0.23	(0.42)	0.25	(0.43)	0.25	(0.43)
U.S. Citizen	0.85	(0.36)	0.86	(0.35)	0.88	(0.32)	0.88	(0.33)
Household Size	2.07	(1.16)	2.08	(1.18)	1.99	(1.04)	2.01	(1.04)
Race								
Non-Hispanic White	0.56	(0.50)	0.54	(0.50)	0.55	(0.50)	0.52	(0.50)
Non-Hispanic Black	0.15	(0.36)	0.17	(0.37)	0.24	(0.43)	0.25	(0.43)
Hispanic	0.19	(0.39)	0.18	(0.39)	0.16	(0.36)	0.17	(0.38)
Education								
Less than High School	0.20	(0.40)	0.19	(0.40)	0.22	(0.42)	0.21	(0.41)
High School	0.32	(0.47)	0.33	(0.47)	0.36	(0.48)	0.36	(0.48)
Some College	0.29	(0.45)	0.28	(0.45)	0.27	(0.44)	0.27	(0.44)
College or Advanced	0.19	(0.39)	0.19	(0.40)	0.15	(0.35)	0.16	(0.36)
Employment								
Hours Worked Last Year	16.50	(18.80)	16.45	(18.75)	18.09	(19.32)	17.78	(19.31)
Does Not Work	0.48	(0.50)	0.48	(0.50)	0.46	(0.50)	0.47	(0.50)
Part-Time	0.26	(0.44)	0.26	(0.44)	0.24	(0.43)	0.23	(0.42)
Full-Time	0.26	(0.44)	0.26	(0.44)	0.30	(0.46)	0.30	(0.46)

Notes: Means are weighted with ACS weights

Table 1.2 shows pre- and post-expansion descriptive information on enrollment for low-income childless adults. The mean rate of Medicaid coverage increased before and after the expansion by roughly 20 percentage points in expansion states. Changes by race/ethnicity in expansion states exhibit small heterogeneity, with increases in Medicaid coverage of 22 percentage points for Whites, 19 percentage points for Blacks, and 19 percentage points for Hispanics. Nevertheless, the disparities in Medicaid coverage narrowed between all racial/ethnic groups, aside from Black adults, who had higher rates of Medicaid coverage in both the pre- and post-reform periods. Gains in employer sponsored insurance (ESI) are slightly greater in non-expansion states in the post expansion period. Meanwhile, gains in non-group private insurance are much higher in non-expansion states compared to expansion states. This is most likely due to the availability of private insurance subsidies for those earning between 100 and 400 percent of the federal poverty line and living in non-expansion states.The uninsured rate decreased by roughly 23 percentage points in expansion states and by 11 percentage points in non-expansion states, highlighting the effectiveness of the expansion.

Table 1.2: Mean Differences in Health Insurance Outcomes Before and After the ACA Medicaid Expansion in Expansion and Non-Expansion States by Race/Ethnicity (0-138% FPL)

	All Low-Income Individuals					
	Expansion States			Non-Expansion States		
	Before	After		Before	After	
	Mean (SD)	Mean (SD)	Diff	Mean (SD)	Mean (SD)	Diff
Medicaid	0.21 (0.41)	0.41 (0.59)	0.20	0.13 (0.34)	0.16 (0.37)	0.03
Employer Sponsored Insurance	0.19 (0.39)	0.19 (0.40)	0.00	0.18 (0.39)	0.21 (0.40)	0.03
Non-Group Private Insurance	0.12 (0.32)	0.13 (0.34)	0.01	0.10 (0.31)	0.17 (0.37)	0.07
Uninsurance Rate	0.47 (0.50)	0.24 (0.43)	-0.23	0.55 (0.50)	0.44 (0.50)	-0.11

	Non-Hispanic White Low-Income Individuals					
	Expansion States			Non-Expansion States		
	Before	After		Before	After	
	Mean (SD)	Mean (SD)	Diff	Mean (SD)	Mean (SD)	Diff
Medicaid	0.18 (0.39)	0.40 (0.49)	0.22	0.11 (0.32)	0.14 (0.35)	0.03
Employer Sponsored Insurance	0.19 (0.39)	0.19 (0.40)	0.00	0.18 (0.39)	0.21 (0.40)	0.03
Non-Group Private Insurance	0.12 (0.32)	0.13 (0.34)	0.01	0.10 (0.31)	0.17 (0.37)	0.07
Uninsurance Rate	0.47 (0.50)	0.24 (0.43)	-0.23	0.55 (0.50)	0.44 (0.50)	-0.11

	Non-Hispanic Black Low-Income Individuals					
	Expansion States			Non-Expansion States		
	Before	After		Before	After	
	Mean (SD)	Mean (SD)	Diff	Mean (SD)	Mean (SD)	Diff
Medicaid	0.31 (0.46)	0.50 (0.50)	0.19	0.19 (0.39)	0.23 (0.42)	0.04
Employer Sponsored Insurance	0.16 (0.37)	0.18 (0.39)	0.02	0.18 (0.39)	0.21 (0.41)	0.03
Non-Group Private Insurance	0.05 (0.23)	0.08 (0.27)	0.03	0.07 (0.25)	0.11 (0.32)	0.04
Uninsurance Rate	0.45 (0.50)	0.22 (0.41)	-0.23	0.53 (0.50)	0.41 (0.49)	-0.12

	Hispanic Low-Income Individuals					
	Expansion States			Non-Expansion States		
	Before	After		Before	After	
	Mean (SD)	Mean (SD)	Diff	Mean (SD)	Mean (SD)	Diff
Medicaid	0.21 (0.41)	0.40 (0.49)	0.19	0.09 (0.29)	0.12 (0.33)	0.03
Employer Sponsored Insurance	0.14 (0.34)	0.16 (0.37)	0.02	0.12 (0.33)	0.17 (0.37)	0.05
Non-Group Private Insurance	0.05 (0.22)	0.07 (0.26)	0.02	0.05 (0.21)	0.12 (0.33)	0.07
Uninsurance Rate	0.59 (0.49)	0.36 (0.48)	-0.23	0.72 (0.45)	0.58 (0.49)	-0.14

Notes: Means are weighted with ACS weights. Standard errors reported in parentheses

1.4 Empirical Methodology

1.4.1 Conceptual Framework

In this section, I introduce a simple framework that estimates the treatment status of individuals based on their eligibility status. This framework was developed by Heckman and Vytlacil (1999) and has recently been applied within the context of health insurance (Abrigo et al., 2021; Kowalski, 2016).[14] I denote treatment status as $D \in \{0, 1\}$. In my case, it corresponds to having Medicaid coverage. Treatment status is determined by a latent variable of the form:

$$I = p_z - U \tag{1.1}$$

where p_z represents the benefits of treatment and U the costs of treatment. The term p_z is determined by a binary treatment assignment variable $Z \in \{0, 1\}$ and is interpreted as eligibility into Medicaid under the 2014 ACA Medicaid expansion. Intuitively, individuals with lower levels of U will accept the treatment relative to those with higher values. I assume U to be a uniform random variable distribution. The term p_z can take on two possible values: p_1 (the probability of treatment for those assigned to treatment, $Z = 1$) and p_0 (the probability of treatment for those not assigned to treatment, $Z = 0$). I assume that U and Z are distributed independently. Participation (Medicaid coverage) is then determined by $D = 1(I \geq 0)$.

Using methodology from Abadie (2002), I adopt a two-sided non-compliance framework dividing the population into three classes: always takers, never takers, and compliers.[15] Figure 1.1 summarizes the treatment take-up across the population based the benefits p_z and costs U of treatment discussed in the previous section. First, if we observe $D = 1$ and $Z = 0$ for an individual, they we can identify them an always taker in the data.[16] The always takers are those with $0 \leq U < p_0$ and will enroll in Medicaid ($D = 1$) even when residing in a state that did not elect to participate in the ACA Medicaid expansion ($Z = 0$).[17] Next,

[14]Unlike Angrist et al. (1996), I am not using treatment status as an IV to estimate the local average treatment effect (LATE) in outcomes. The model is simplified by estimating only the "first stage," or in this case, treatment status.

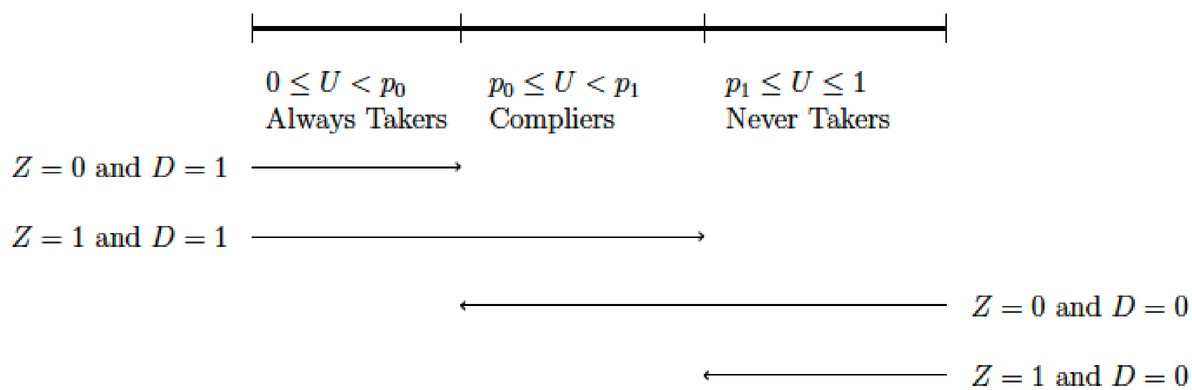
[15]In a two-sided non-compliance framework, there is a 4th class, defiers, who receive treatment if assigned to the control and do not receive treatment if assigned to treatment. I exclude the defiers from the analysis under the assumption of monotonicity.

[16]Note that this is a necessary, but not a sufficient condition.

[17]The always takers could also include individuals that qualified for Medicaid via Supplemental Security Income (SSI) benefits or through state Medicaid programs that existed before the enactment of the 2014 ACA Medicaid expansion.

individuals with $p_0 \leq U < p_1$ are the compliers. The compliers will enroll in Medicaid ($D = 1$) if they are eligible under the expansion ($Z = 1$) and will not enroll if otherwise. However, compliers cannot be identified separately in the data as they are indistinguishable from the always takers and never takers when $Z = D$. For example, individuals with $Z = 1$ and $D = 1$ includes both the always takers and treated compliers. Similarly, individuals with $Z = 0$ and $D = 0$ includes both the never takers and untreated compliers. Lastly, if we observe $D = 0$ and $Z = 1$ for an individual, they we can identify them as a never taker in the data. The never takers are those with $p_1 \leq U \leq 1$ and will never enroll in Medicaid ($D = 0$) even when residing in a state that has participated in the expansion at time t ($Z = 1$).[18]

Figure 1.1: Treatment Groups from Complier Analysis



Source: Abrigo et al. (2021)

1.4.2 Complier Characteristics

In this section, I employ complier analysis to estimate the characteristics of the compliers, those who became eligible under the expansion and enrolled in Medicaid. The identification of the compliers can help policymakers understand how the ACA expansion affected Medicaid take-up across various demographics.

As discussed in the previous section, the compliers cannot be separately identified in the data. Therefore, to estimate the characteristics of the compliers (i.e., $E[X \mid D = d, p_0 \leq U < p_1]$ for $d \in \{0, 1\}$), I utilize methods from Abrigo et al. (2021) and Kowalski (2016) to solve for the weighted sum of the averages of the characteristics for both the untreated

[18] The never takers could also consist of individuals who opted not to enroll in Medicaid due to being covered under ESI or non-group private coverage.

and treated compliers. I begin by noting that $Z = D$ for $U \in [p_1, p_0]$. I also assume that $Z \perp (U, X)$, i.e., treatment is unrelated to cost or any observable. Following Abadie (2003) and Kowalski (2016) the average characteristics of the untreated compliers can be estimated by the following equation:

$$\begin{aligned}\mu_x(0) &= E(X \mid D=0, p_0 \leq U < p_1) = E(X \mid Z=0, p_0 \leq U < p_1) \\ &= \frac{1}{(p_1 - p_0)}\left[E(X \mid Z=0, D=0)\,(1-p_0) - E(X \mid Z=1, D=0)\,(1-p_1)\right]\end{aligned} \tag{1.2}$$

where AT represents the always takers, NT represents the never takers, C represents the compliers, and NTUC represents the combination of the never takers and untreated compliers.

The average characteristics for the treated compliers can be estimated in a similar fashion with the following equation:

$$\begin{aligned}\mu_x(1) &= E(X \mid D=1, p_0 \leq U < p_1) = E(X \mid Z=1, p_0 \leq U < p_1) \\ &= \frac{1}{(p_1 - p_0)}\left[E(X \mid Z=1, D=1)\,p_1 - E(X \mid Z=0, D=1)\,p_0\right]\end{aligned} \tag{1.3}$$

where ATTC represents the combination of the always takers and the treated compliers. The benefits of treatment p_1 and p_0 in equations (1.2) and (1.3) are derived from a difference-in-differences regression that estimates the direct effects of the expansion on Medicaid coverage. This will be discussed further in section 1.4.3. To derive the average characteristics of the compliers, I take the weighted sum of the solutions to equations (1.2) and (1.3).[19]

Following Abrigo et al. (2021) and Kowalski (2016), I perform a simple linear regression that regresses some observable X_{ist} onto indicators terms for the never takers (NT), the always takers (AT), the combination of the always takers and treated compliers $(ATTC)$, and the combination of the never takers and untreated compliers $(NTUC)$. I estimate the following regression:

$$X_{ist} = \lambda_{NT} + \lambda_{AT}\,1(AT_{ist}) + \lambda_{AT+TC}\,1(ATTC_{ist}) + \lambda_{NT+UC}\,1(NTUC_{ist}) + \gamma_t + \phi_s + u_{ist} \tag{1.4}$$

The conditional expectations required to estimate the expectations in equations (1.2) and (1.3) are provided by the coefficients for each of the indicator terms. The coefficient λ_{NT} estimates $E(X|Z = 1, D = 0)$ in equation (1.2) and serves as the constant or intercept

[19] I chose the weights that minimize the variance of the weighted average.

in the regression. Similarly, λ_{AT} estimates $E(X|Z = 0, D = 1)$ in equation (1.3), λ_{AT+TC} estimates $E(X|Z = 1, D = 1)$ in equation (1.3), and λ_{NT+UC} estimates $E(X|Z = 0, D = 0)$ in equation (1.2). I include year (γ_t) and state (ϕ_s) fixed effects to control for differences across states and time.

1.4.3 Difference-in-Differences

Main Specification

My empirical strategy leverages the variation in states' decisions to expand Medicaid under the ACA expansion in 2014 to assess the effects of the provision on the probability of receiving Medicaid coverage for low-income childless adults. I use a difference-in-differences (DID) model with staggered treatment to estimate the effects of the ACA Medicaid expansion on Medicaid coverage. I run the following regression:

$$D_{ist} = \beta_0 + \beta_1 Z_{st} + \beta_2 X_{ist} + \gamma_t + \phi_s + \epsilon_{ist} \tag{1.5}$$

where D_{ist} represents a binary indicator for whether individual i living in state s is covered under Medicaid at time t. The variable Z_{st} is a treatment variable that equals 1 if individual i resided in a state s that expanded Medicaid at time t, and 0 otherwise. This term is turned on the year after the enactment, as some states expanded later in the year or in subsequent years. Therefore, Z_{st} reflects the variation in the timing of states' decisions to expand Medicaid eligibility. I define a state to have expanded in the current year if they have done so on or prior to July 1st.[20]

All individuals whose incomes are less than 138% of the FPL are eligible for Medicaid if they reside in a state that adopted the Medicaid expansion at time t, but not all of them enroll. However, individuals are likely to possess predisposing and enabling characteristics that can potentially serve as barriers to enrollment and affect their decision to seek health coverage (Andersen et al., 2007). In a related example, the randomized control trial in the Oregon health insurance experiment had only 30% of eligible individuals enroll in Medicaid (Baicker et al., 2013; Finkelstein et al., 2012). Hence Z_{st} captures the intent-to-treat (ITT) effect of being eligible for Medicaid via the state's adoption of the expansion.

[20]There are 6 states: AK, IN, LA, MT, NH and PA that expanded Medicaid after July 1st, 2014. I define states PA (January 1, 2015), IN (February 1, 2015), and NH (August 15, 2014) to have expanded in 2015. I define the remaining states AK (September 1, 2015), MT (January 1, 2016), and LA (July 1, 2016) as having expanded in 2016.

The coefficient β_1 measures the magnitude of the difference in $(p_1 - p_0)$ and captures the potential increase in Medicaid enrollment for those who became eligible under the Medicaid state expansion. The estimates of p_1 and p_0 from equation (1.5) are the propensity scores that correspond to the benefits of treatments described in section 1.4.1 and are used to solve for the average characteristics of the treated and untreated compliers in equations (1.2) and (1.3). The term X_{iast} represents a set of observables such as work status, race/ethnicity and educational attainment. Lastly, I include year and state fixed effects that are represented by γ_t and ϕ_s, respectively. The fixed effects adjust for time invariant state-specific heterogeneity and contemporaneous shocks. To account for possible serial correlation, I cluster all standard errors at the state level.

Testing Parallel Trends

The key assumption of a DID design is the parallel trends assumption, which states that Medicaid enrollment would have evolved similarly between the treated and control states in the absence of the ACA expansion, after controlling for individual-level demographics, year, and state fixed effects. To test the validity of the DID design, I adopted an event study framework similar to Miller et al. (2021) that assessed the changes in health insurance outcomes while controlling for fixed differences across states and national trends over time. The specification for the event study is as follows:

$$D_{ist} = Z_{st} \times \sum_{\substack{y=-4 \\ y \neq -1}}^{3} \beta_y I(t - t_s^* = y) + \beta_x X_{ist} + \gamma_t + \phi_s + \epsilon_{ist} \tag{1.6}$$

where y is equal to the difference between the year observed and treatment period for state s. The indicator term $I(t - t_s^* = y)$ measures the time relative to the year a state expanded Medicaid, t_s^*, and equals zero in all periods for non-expansion states. I set $y = -1$, the year prior to the expansion, to be the omitted period. I "trimmed" the data by omitting values for $y < -4$ since I observe $y < -4$ only for late expansion states.[21] This addresses the issue of multicollinearity arising from the linear relationship between the two-way fixed effect estimator (TWFE) and the relative time period indicators. The coefficient β_y provides the change in Medicaid coverage in expansion states relative to non-expansion states in the year y, measured from the year immediately prior to expansion. If the values for β_y when

[21] As a robustness check, I "binned" the data by grouping all distant leads and lags into one indicator. My results did not significantly differ from what was reported in the main result.

$y < 1$ is close to zero and statistically insignificant, then the parallel trends assumption holds. I estimate equation (1.6) using a linear probability model with ACS survey weights and cluster the standard errors at the state level.[22]

1.4.4 Estimating the Probability of Being A Complier

In this section, I estimate the conditional probability of being a complier, i.e., the conditional likelihood of being induced by the ACA expansion to enroll in Medicaid, by first noting that this can be inferred from the following observation information Abadie (2003):

$$
\begin{aligned}
Pr(p_0 \leq U < p_1 \mid X) &= 1 - Pr(D = 0 \mid X) - Pr(D = 1 \mid X) \\
&= \underbrace{1 - Pr(D = 0 \mid Z = 1, X)}_{=p_1} - \underbrace{Pr(D = 1 \mid Z = 0, X)}_{=p_0} \\
&= \underbrace{Pr(D = 1 \mid Z = 1, X)}_{=p_1} - \underbrace{Pr(D = 1 \mid Z = 0, X)}_{=p_0}
\end{aligned}
\tag{1.7}
$$

where the second equality holds by independence of treatment assignment Z.[23] Note that the benefits of treatment p_1 and p_0 can also be inferred from equation (1.7). As outlined in figure 1.1, the conditional probability of being an always taker, those who qualified for Medicaid prior to the expansion and enrolled, can be obtained from p_0 or $Pr(D = 1 \mid Z = 0, X)$. Similarly, the conditional probability of a never taker, those who didn't enroll into Medicaid despite being eligible under the expansion, can be obtained from $1 - p_1$ or $1 - Pr(D = 1 \mid Z = 1, X)$.

It is important to note that the difference-in-differences approach outlined in equation (1.5) only provides the unconditional estimates of p_1 and p_0. Therefore, I modify equation (1.5) into a saturated probit model that interacts Medicaid expansion status Z_{st} with demographic variables relating to work status, race/ethnicity, education, and income group. Next, I predict the propensity scores from my model and condition them based on my demographic

[22]Some have raised concerns about interpreting the casual effects in a DID with staggered treatment as there are violations of strict exogeneity that result in a biased DD estimate (Goodman-Bacon 2021 and Sun and Abraham 2021). To address this, I perform several robustness checks in section A.3 in the appendix using the techniques introduced in these studies to evaluate whether staggered treatment is a concern in my design. Figure A.9 reports my results using the methods from Sun and Abraham (2021), while figure A.10 and table A.5 report those from Goodman-Bacon (2021).

[23]This is specifically noted in Lemma 2.1 in Abadie (2003).

variable of interest. Then, I apply equation (1.7) and solve for the conditional probability of being a complier. My findings for work status and race/ethnicity are reported in the main paper, while those for education and income group are in the appendix.[24]

Lastly, it is important for policymakers to consider the impacts of the expansion on Medicaid coverage at the state-level. Therefore, I estimate equation (1.7) for each state. However, I am unable to observe $Pr(D = 1 \mid Z = 1, X)$ or p_1 in states that have not expanded Medicaid. I address this by predicting the counterfactual: the probability of being a complier if a non-expansion state had actually expanded Medicaid. The added value of my methodology is that it allows policymakers to assess which populations were more likely to be induced by the expansion to seek Medicaid in each state, a phenomenon that cannot be fully explained by traditional difference-in-differences methods alone, i.e., equation (1.5). Furthermore, deriving the counterfactual can inform policymakers about the potential beneficiaries of expanding Medicaid in non-expansion states.

I summarize the methodology of my paper in the following steps: First, I run the regression in equation (1.5) to predict the propensity scores or benefits of treatment p_1 and p_0. Second, I estimate the class conditional expectations of the always takers, never takers, and their composites with the treated and untreated compliers for each of the observables using equation (1.4). Third, I utilize the estimates from the previous steps alongside equations (1.2) and (1.3) to calculate the conditional expectations of the compliers with the optimal weights. Finally, I run a saturated probit model and apply equation (1.7) to estimate the probability of being a complier at both the aggregate and state-level.

1.5 Results

1.5.1 Estimating the Probability of Medicaid Take-up

In Table 1.3, I provide the results from the DID regression in equation (1.5) on the effects of the ACA Medicaid expansion on health coverage. Columns (1) - (4) provide the

[24] Although there are possibility endogeneity concerns with work status, I argue that this is unlikely as previous research has found minimal effects of the ACA expansion on labor supply (Garrett et al., 2017; Gooptu et al., 2016; Kaestner et al., 2017; Leung and Mas, 2018; Moriya et al., 2016). Frean et al. (2017) raised identification concerns relating to income due to the possibility of omitted factors that correlate income with preferences for insurance. Furthermore, they have raised concerns regarding survey-reported income, which is subject to measurement error. Therefore, I have acknowledged these concerns by reporting all results relating to income group in the appendix.

results for childless adults with incomes below 138% of the FPL on the propensity of having either Medicaid coverage, ESI, non-group private insurance, or being uninsured, respectively. Each cell in the sample reports the coefficient on states' expansion status interacted with a post treatment dummy, $Z_{st} = POST_t \times Expand_s$.

Table 1.3: The Effects the ACA Medicaid Expansion on Health Insurance Coverage for Childless Adults

	(1) Medicaid	(2) ESI	(3) Purchased	(4) Uninsured
Expanded	0.157***	-0.017***	-0.046***	-0.092***
	(0.016)	(0.005)	(0.007)	(0.016)
Observations	706361	706361	706361	706361
Year FEs	✓	✓	✓	✓
State FEs	✓	✓	✓	✓

Notes: Sample is restricted to non-disabled childless adults aged 26-64. Standard errors are clustered at the state-year level and are provided in parentheses (*** p<0.01, ** p<0.05, * p<0.10). Each cell reports the results from regressing the main effects of policy variables outlined in equation (1.5) and several controls on different types of health insurance indicators across two different income samples. Controls include gender, race/ethnicity, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All regressions control for state and year fixed effects. All estimates are weighted using ACS weights.

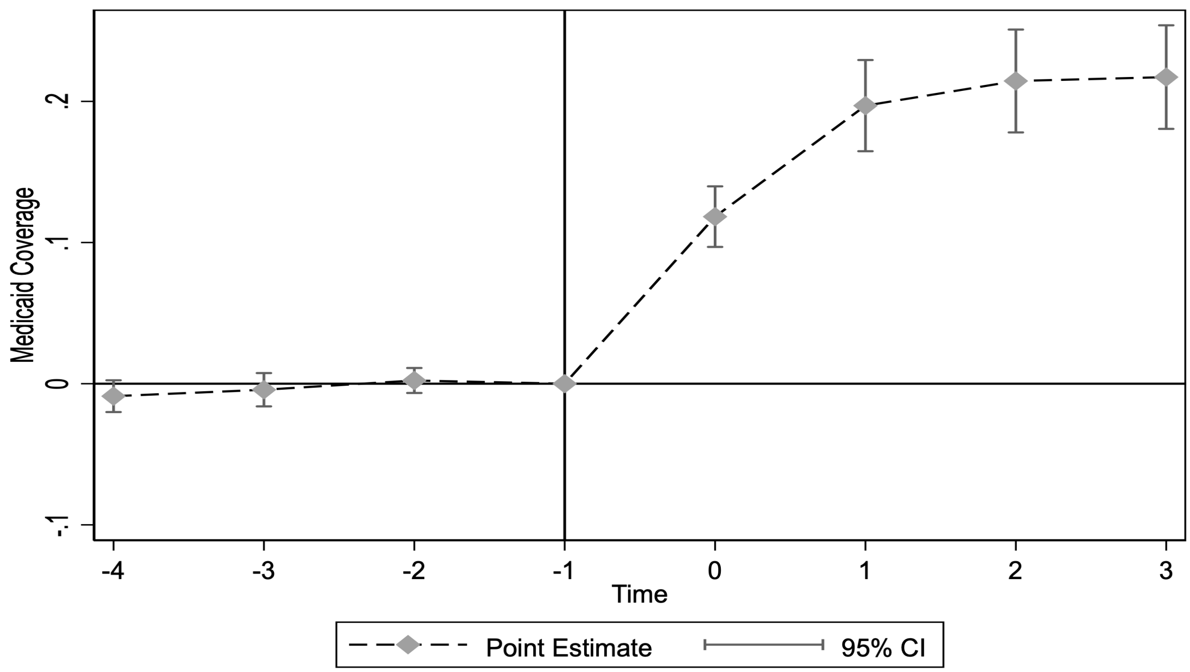
The estimated effect of the basic DID specification shows that the ACA expansion led to statistically significant increases in Medicaid coverage of approximately 15.7 percentage points. The differences in the size of the estimates are likely explained by the fact that the sample below 138% of the FPL includes the population most likely targeted in the expansion. Past studies found that the ACA Medicaid expansion led to increases in Medicaid coverage ranging from 2 to 15 percentage points (Courtemanche et al., 2017; Duggan et al., 2019; Frean et al., 2017; Leung and Mas, 2018; Simon et al., 2017; Wherry and Miller, 2016). Given both my sample restrictions and the longer time period, this results in the size of my estimates being slightly higher than what is reported in the literature.

I see some evidence of crowding out in private health insurance. The Medicaid expansion reduced ESI by approximately 1.7 percentage points. Reductions in non-group private insurance were approximately 4.6 percentage points. In both subgroups, the coefficients for private insurance and the uninsured rate nearly equal the amount reported for Medicaid, indicating that there is little evidence that beneficiaries are dual enrolling in Medicaid and private insurance.[25] My results suggest that among low-income childless adults, approximately 40% of gains in Medicaid can be explained by the crowding out of private coverage and 60% represent individuals acquiring Medicaid coverage. This finding is higher than what was reported in the previous studies for low-income adults, where they observed crowd-out rates ranging from 23% to 33% (Courtemanche et al., 2017; Kaestner et al., 2017). However, it is important to note that both studies did not restrict their samples to low-income childless adults, utilized different empirical strategies, and were more restrictive on which states were considered treated (i.e., states were considered treated only if they expanded with no prior history).

The assumption of parallel trends holds if changes in Medicaid coverage in expansion states evolve similarly to those in non-expansion states in the absence of the ACA Medicaid expansion. Therefore, I utilize the event-study model outlined in equation (1.6) to test this assumption. In addition, the event-study model allows the observation of dynamic treatment effects across time. The results of the event-study are presented in figure 1.2.[26] The point estimates are provided with 95% confidence intervals and are estimated relative to the year prior to when a state adopted the Medicaid expansion.

[25]I test to see if the linear combination of the coefficients sums to zero. I am unable to reject the null.
[26]Detailed results are available in table A.1 in the appendix.

Figure 1.2: Event Study of the ACA Medicaid Expansion (2010-2017)



Notes: This figure reports the coefficients from estimating equation (1.6) with Medicaid coverage as the outcome variable. The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% of the FPL. Controls include gender, race/ethnicity, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates are weighted using ACS weights.

During the pre-period, I found that the ACA expansion had near-zero and insignificant effects on all health insurance variables.Therefore, my estimates are consistent with the parallel trends assumption. I see positive and statistically significant changes in Medicaid coverage over time in the post-period.These increases potentially reflect heightened awareness, individual mandates, reductions in enrollment barriers, and improvements in outreach strategies brought about by the ACA and directed at low-income childless adults. Consistent with the main results of the DID regression outlined in equation (1.5), I observe negative and statistically significant changes in private coverage and the uninsured rate.

1.5.2 Complier Characteristics

I compute the average characteristics of the compliers and compare them to those of the never takers and always takers using the parameters from equation 1.4. As stated in section 1.4.1, the compliers were those who received Medicaid through the expansion, the always takers were those who were eligible prior to the expansion through special waivers, SSI benefits, and other state programs, and the never takers did not seek coverage despite being eligible for the expansion. Figure 1.3 reports the results on indicators for work status and race/ethnicity. Additional results on indicators for gender, income group, and education are reported in figure A.3 in the appendix.[27] Each graph plots the means and 95% confidence intervals calculated from 1000 bootstrapped re-samples. I report my estimates for always takers, compliers, never takers, and unconditional means separately. Due to the large sample size of the ACS, the estimates do not exhibit much noise, resulting in the small size of the confidence intervals. However, as the compliers cannot be separately identified in the data and require many computational steps, they make up a smaller fraction of the overall sample and are noisier in comparison to the other groups.

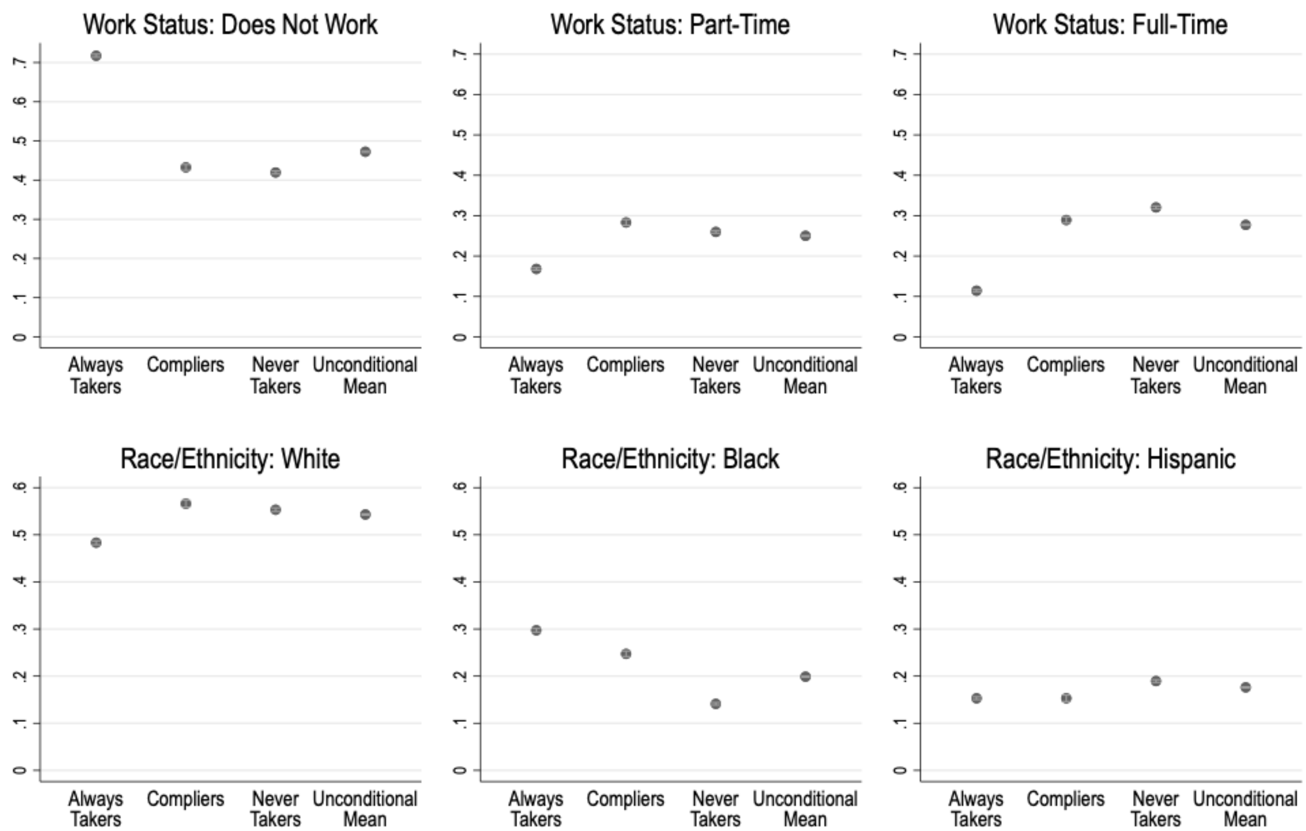
According to figure 1.3, the compliers were primarily part-time workers as the means of the compliers for part-time workers were above those of the never takers and always takers. Those who do not work were disproportionately always takers, whereas full-time workers were disproportionately never takers. Evaluating by race/ethnicity, the compliers were more likely to be white, as their means were higher than those of the never takers and always takers.Blacks were disproportionately always takers, as the means of the compliers were above those of the never takers, but below those of the always takers. Hispanics were disproportionately never takers, as the means of the compliers were above those of the always takers, but below those of the never takers.

There are a few takeaways from performing a complier analysis in the context of the ACA Medicaid expansion. First, the compliers are mainly those from the middle of the distribution for work status. Those not working likely acquired Medicaid coverage either through medically needy pathways, or from state Medicaid programs that existed prior to the expansion and generously covered low-income childless adults in severe poverty. Those working full-time likely received ESI coverage through work; therefore, they opted not to seek Medicaid. However, those who worked part-time were unable to qualify for ESI coverage, thereby inducing them to enroll in Medicaid. In short, individuals on both sides of the distribution for work status already qualified for insurance, providing context as to why those in the middle are more likely to be compliers.[28]

Second, I've found that the compliers were disproportionately White, the always takers

[27] Tabulated versions of these figures are reported in tables A.2 in the appendix.
[28] This pattern is also consistent with education, as shown in figure A.3.

Figure 1.3: Observable Characteristics for the Always Takers, Compliers, and Never Takers: Childless Adults (0-138% FPL)



Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

were disproportionately Black, and the never takers were disproportionately Hispanic. My findings for Blacks are consistent with the literature, demonstrating that they have historically relied heavily on Medicaid as a continuous source of health coverage. Additionally, the poverty rate for this group is almost three times higher than the poverty rate observed for White individuals, thus granting them access to Medicaid through SSI benefits and state programs dating before the establishment of the ACA (DeNavas-Walt et al., 2013). My findings for Hispanics could be explained by previous research that documents Hispanics' negative attitudes toward public coverage, difficulties with Medicaid enrollment processes, and additional barriers related to accessibility, financial burden, and perceived need (Allen et al., 2014; Andersen et al., 2007; Michener, 2020; Sommers et al., 2012; Weech-Maldonado et al., 2003).

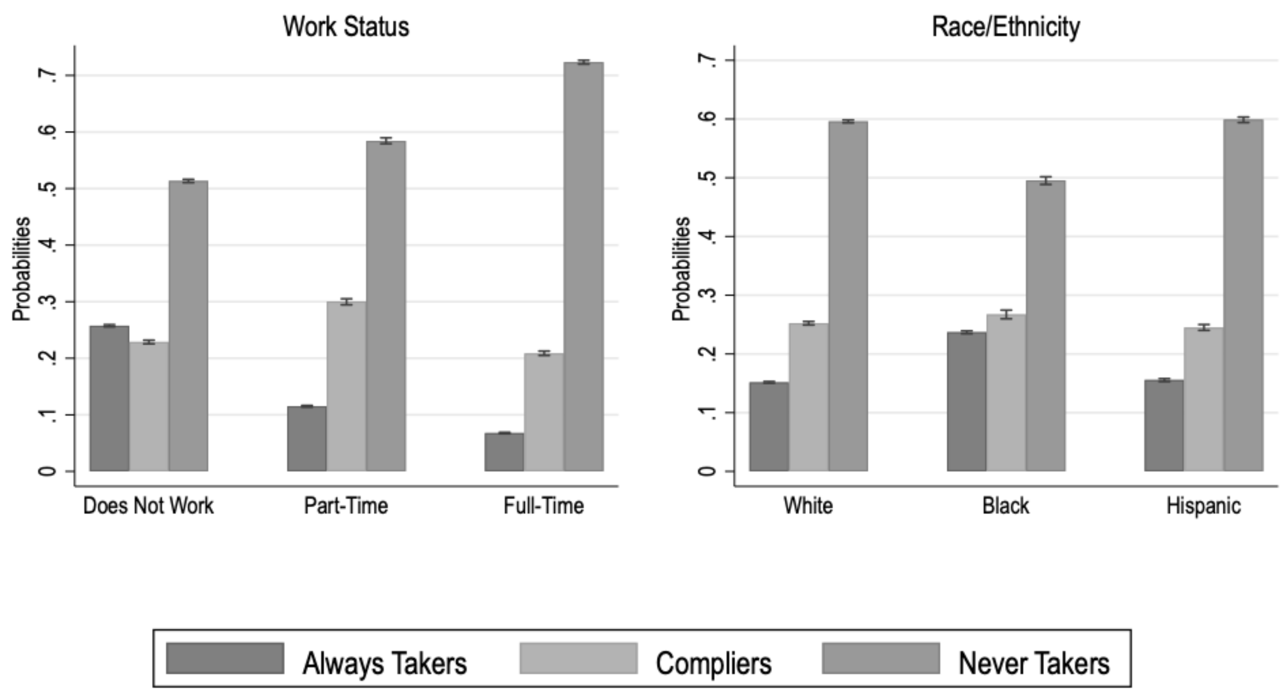
1.5.3 Conditional Probability of Being A Complier

In this section, I employ saturated probit and methods from Abadie (2003) to estimate the conditional probability of being a complier, i.e., the likelihood of obtaining Medicaid coverage for a low-income childless adult if they resided in a state that expanded Medicaid between 2014 and 2017. In addition to the compliers, I estimate the conditional probability of being an always taker, i.e., the likelihood of having Medicaid coverage as a result of being eligible for Medicaid prior to the expansion, and a never taker, i.e., the likelihood of not having Medicaid coverage despite residing in a state that expanded Medicaid between 2014 and 2017. I present results by work status and race/ethnicity in separate panels in figure 1.4. I also provide the results for income group and education in figure A.4 in the appendix. Each panel contains the mean probabilities and 95% confidence intervals computed from 1000 bootstrapped re-samples for the always takers, compliers, and never takers.

In the left panel of figure 1.4, I find that part-time workers are more likely to be compliers than non-workers and full-time workers, suggesting that the Medicaid expansion itself was responsible for inducing mainly part-time workers to enroll in Medicaid. As a result, this characterization of the compliers does not conform to what defines the "undeserving poor", given that they work at least part-time. Moving from non-workers to full-time workers, I observe positive and negative gradients in the probability of being a never taker and an always taker, respectively. These estimates demonstrate the same patterns observed in the conditional means derived under the complier analysis in figure 1.3.

In the right panel, there are no discernible differences in the probability of being a

Figure 1.4: Conditional Probabilities of the Always Takers, Compliers, and Never Takers: Work Status and Race/Ethnicity, Childless Adults (0-138% FPL)



Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

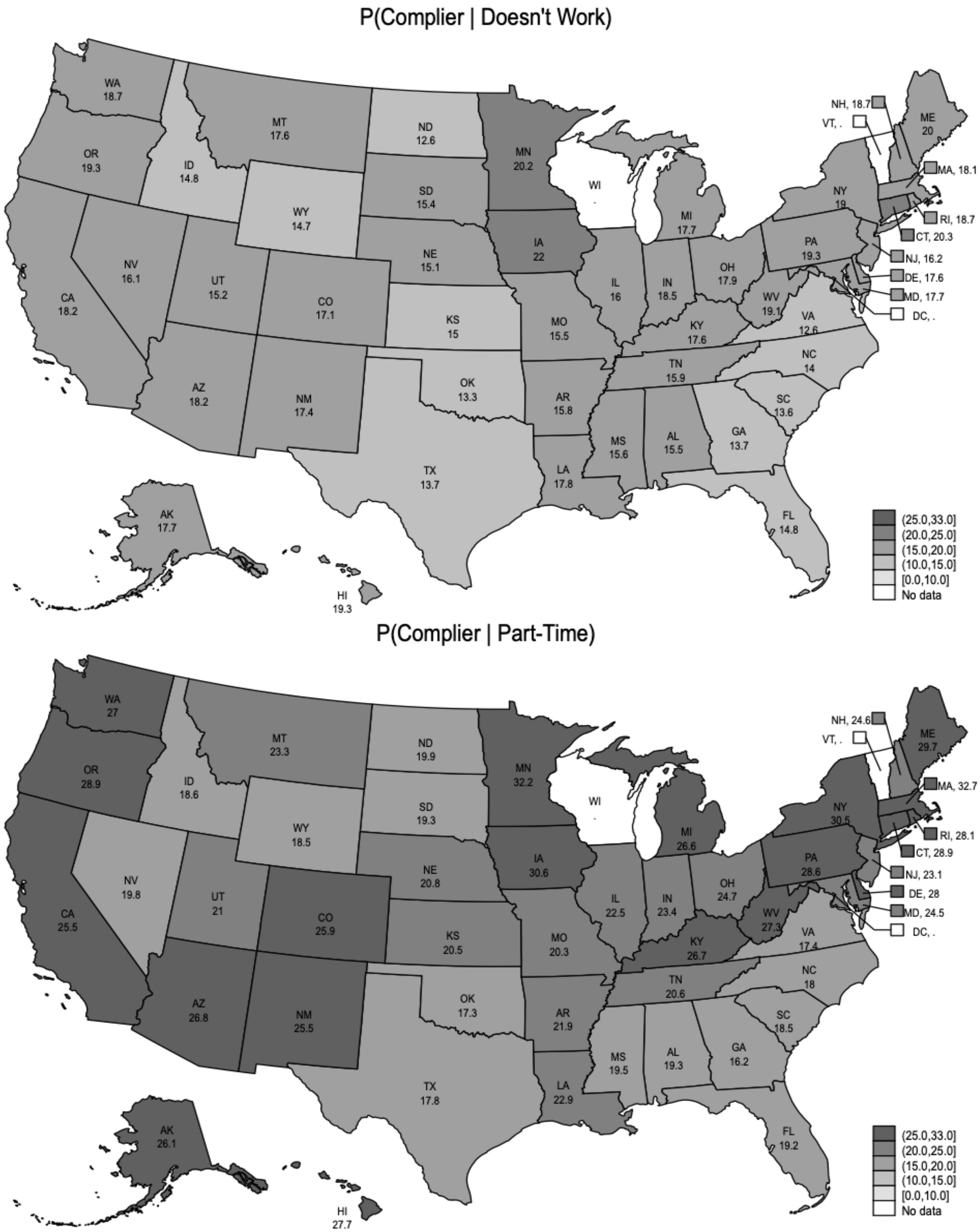
complier by race/ethnicity. This contrasts with the conditional means presented in figure 1.3, where the complier means for Whites were above those of the always takers and never takers, while the complier means for Blacks were below those of the always takers. While figure 1.3 that the compliers were disproportionately White, this is not the case in figure 1.4. My estimates support previous research showing that the racial disparities in health coverage among the low-income population have narrowed but have not been completely eliminated (Courtemanche et al., 2016; Courtemanche et al., 2017; Courtemanche et al., 2019; Lee and Porell, 2020). Across all racial/ethnic groups, Blacks were the most likely group to be always takers and the least likely group to be never takers, which is consistent with figure 1.3. It is important to note, however, that for Blacks, the high likelihood of being an always taker is a pre-treatment outcome and thus cannot be causally identified. This is supported by table 1.2, where Medicaid coverage prior to the expansion was highest among Blacks in both expansion and non-expansion states. Hispanics and Whites appear equally likely to be always takers or never takers, but this contradicts my findings in figure 1.3, where the never takers were predominantly Hispanic not White. This could suggest that there are other factors unobserved and could influence the desire of White individuals to seek Medicaid in addition to those previously mentioned for Hispanics.[29]

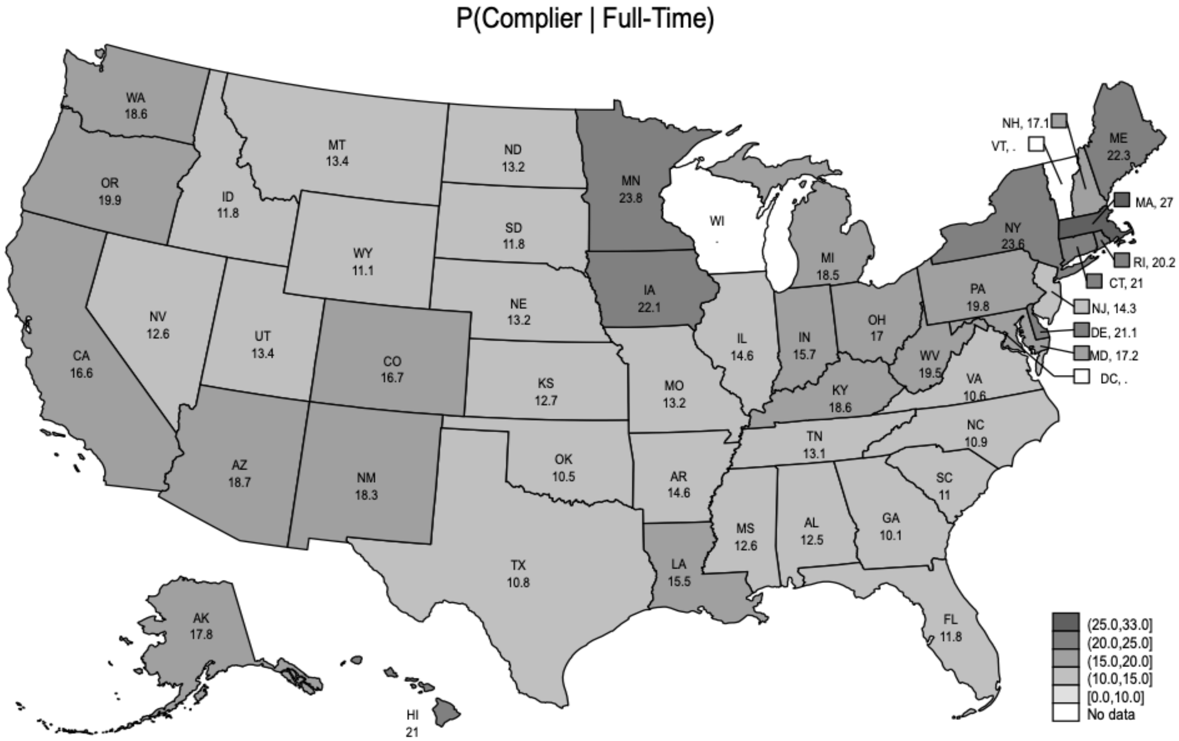
I now report the complier probabilities at the state level. These estimates also include the counterfactual for non-expansion states, i.e., the probability of being a complier if the state had participated in the expansion in 2014. I report the state-level estimates by work status in figure 1.5. Across all states and DC, the probability of being a complier is higher for part-time workers compared to non-workers and full-time workers. This includes all non-expansion states, as well as those that previously enacted work requirements under Section 1115 demonstration waivers (AR, KS, KY).Additionally, there are only marginal differences in the probability of being a complier between non-workers and full-time workers across all states. Lastly, the probability of being a complier is smaller in non-expansion states compared to expansion states. This is supported by figure A.5 where the probability of being an always taker is higher in these states, whereas figure A.6 shows that the probability of being a never taker is higher in non-expansion states. The differences observed by expansion status could be attributed to the fact that the ACA included provisions that enhanced enrollment procedures and promoted outreach programs in states that adopted the expansion. On the other hand, this could highlight potential barriers relating to accessibility, awareness, and perceived need

[29]Furthermore, the never takers include those who have private insurance, and given that White people were most likely to have private insurance according to table 1.2, this could explain why they are also highly likely to be never takers.

that primarily exist in non-expansion states and would prevent individuals from seeking and obtaining Medicaid coverage.

Figure 1.5: State-Level Conditional Probabilities of the Compliers: Work Status, Childless Adults (0-138% FPL)





Notes: I report the estimates on the probability of being a complier for each state using a saturated probit model and methods from Abadie (2003). These include counterfactual estimates for non-expansion states or the probability of being a complier if that state had expanded Medicaid in 2014. Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

I present the state-level complier probabilities for race/ethnicity in figure 1.6. Figures A.7 and A.8 in the appendix display the results for the always takers and never takers, respectively. Initially, there appeared to be no discernible differences in the likelihood of being a complier across race/ethnicity, with the exception of estimates being slightly lower for Hispanics overall. However, when analyzing the estimates for the ten states that haven't expanded Medicaid as of January 1st, 2023 (AL, FL, GA, KS, MS, NC, SC, TN, TX, WY)[30], the probability of being a complier is higher for Blacks than Whites in nine of them, with the exception of Wyoming (WY). It is important to note that in these nine states, Black individuals comprise 8–55.8% of their state's population, while Wyoming (WY) only holds 1.4% of this population.[31] When concentrating on the top ten states (AL, AR, DE, GA, LA,

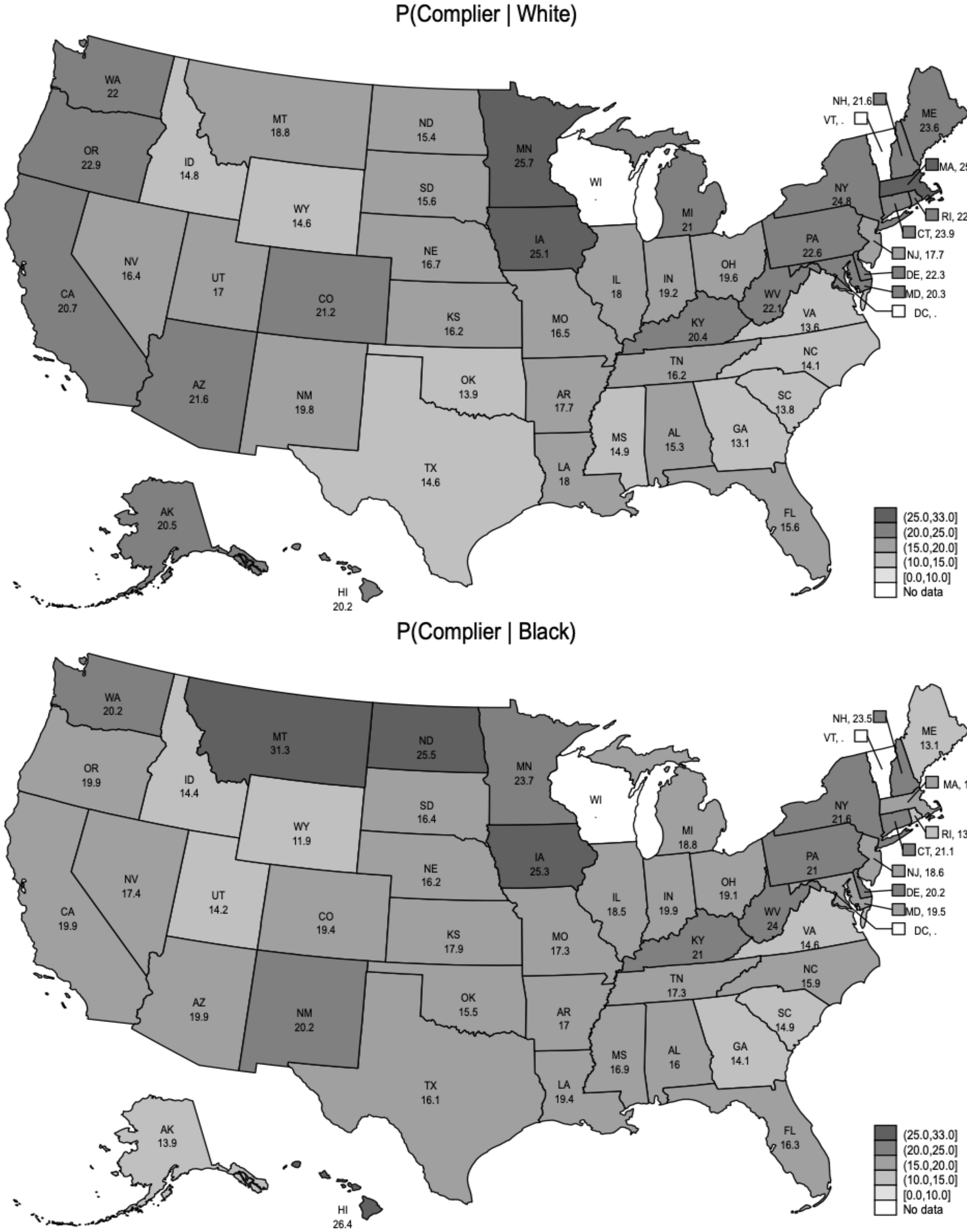
[30]Wisconsin (WI) has yet to fully expand Medicaid as of January 1st, 2023. However, as previously mentioned, they expanded their eligibility criteria to those below 100% of the FPL. Therefore, I do not observe Wisconsin (WI) in my results.

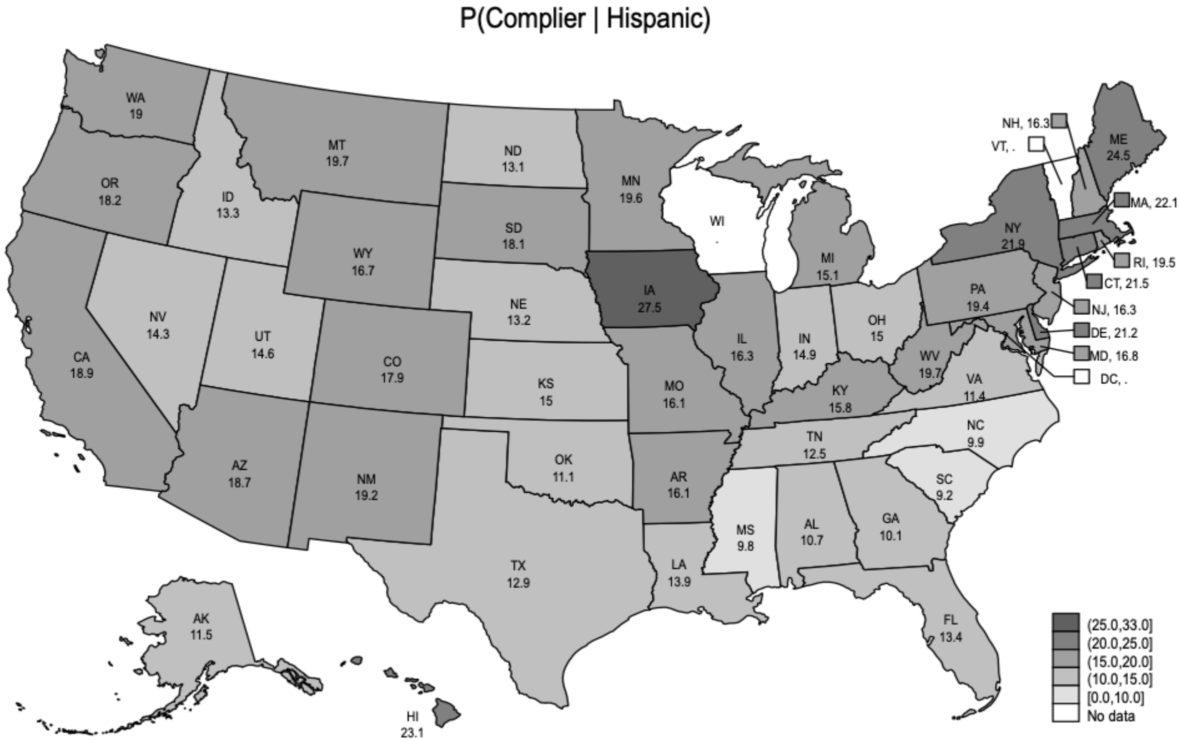
[31]I report the differences in the complier probabilities for Blacks and Whites for these states in table A.3 in the appendix. In addition, I include the percentage of Black individuals who reside in these states. These percentages were estimated from my sample of low-income childless adults with incomes ranging between 0-138% of the FPL.

MD, MS, NC, SC, VA) with the highest Black populations, the complier probabilities are higher for Blacks compared to Whites in seven of them (AL, GA, LA, MS, NC, SC, VA), yet only Louisiana (LA) participated in the expansion by 2017.[32] In the three remaining states (AR, DE, MD), the probability of being a complier is higher for White individuals with each of these states expanding between 2014 and 2017. Therefore, my estimates suggest that Blacks would be the largest beneficiaries if any expansions of Medicaid were to take place in the remaining non-expansion states.

[32] I report the differences in the complier probabilities for Blacks and Whites for these in table A.4 in the appendix. In addition, I include the percentage of Black individuals who reside in these states and the year each state expanded Medicaid, if applicable. These percentages were estimated from my sample of low-income childless adults with incomes ranging between 0-138% of the FPL.

Figure 1.6: State-Level Conditional Probabilities of the Compliers: Race/Ethnicity, Childless Adults (0-138% FPL)





Notes: I report the estimates on the probability of being a complier for each state using a saturated probit model and methods from Abadie (2003). These include counterfactual estimates for non-expansion states or the probability of being a complier if that state had expanded Medicaid in 2014. Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

1.6 Policy Implications and Conclusion

This paper provides the first estimates on the conditional probability of being a complier in the ACA Medicaid expansion. Additionally, this is the first study that has attempted to apply this with respect to policy analysis. Using national data from the ACS, I employed methods from Abadie (2003) to identify the types of individuals that were likely to be induced by the Medicaid expansion to enroll.

Consistently across all states, the probability of being a complier was highest for part-time workers compared to full-time workers and non-workers. I also discovered that in non-expansion states with large Black populations, the probability of being a complier is higher for Blacks than for Whites or Hispanics. Moreover, I find that in states with the highest percentage of Black individuals, the probability of being a complier is higher for Whites in states that actually expanded Medicaid between 2014 and 2017. These results suggest that if Medicaid were to expand in the remaining non-expansion states, the largest beneficiaries would be both part-time workers and Black individuals.

The findings of this paper have significant policy implications for the future of Medicaid. States are currently engaging in efforts to waive restrictions against imposing work requirements under Section 1115 demonstration waivers as a determination for Medicaid eligibility. These work requirements may result in many Medicaid recipients becoming newly ineligible, thus exacerbating the coverage gap further. A previous study found that the implementation of the work requirements in Arkansas led to significant losses in Medicaid coverage and increases in the percentage of adults who are uninsured (Sommers et al., 2019). Consequently, the implementation of these waivers could have serious consequences for an otherwise vulnerable population. Therefore, my findings call into question the motivation behind the implementation of work requirements under the Section 1115 demonstration waivers, as the compliers in every state, including those that have already implemented work requirements, cannot be identified with the characteristics that define the "undeserving poor."

Expanding Medicaid is critical for Black people as they reside disproportionately in non-expansion states, leaving many of them without affordable options for health coverage (Artiga et al., 2016). My findings suggest that if Medicaid were to expand in the remaining non-expansion states, the largest beneficiaries would be Black individuals. Yet in the states with the highest Black populations, where Medicaid expansion has actually occurred, the beneficiaries were primarily White individuals. This provides a clearer context as to why disparities in health coverage are still present across race/ethnicity. My findings could highlight potential racial/ethnic biases that hindered efforts to address the coverage disparities that exist for Black individuals. One study found that in states where White respondents' willingness to accept the Medicaid expansion was low, a high Black demographic was associated with a decreased likelihood of a state accepting the expansion (Grogan and Park, 2017). In a laboratory study, participants not only deemed typical welfare recipients to be Black individuals, but they also perceived them to be less deserving of welfare compared to other races (Brown-Iannuzzi et al., 2017). My estimation of the compliers suggests that expanding Medicaid in all remaining states could help to close the coverage gap that is disproportionately borne by Black individuals, though other efforts to address racial/ethnic discrimination against Medicaid recipients are warranted.

This paper has only "scratched" the surface by focusing on health coverage rather than health services. However, given that health insurance has been linked to better access and receipt of care, reductions in mortality, and improvements in health status and financial security (Sommers et al., 2017), expanding Medicaid in states that have yet to do so will not only provide health insurance to many low-income childless adults trapped in the coverage gap, but will also assist in addressing the health disparities that are prevalent for low-income individuals. This paper is also limited in that it makes no effort to establish why certain individuals are compliers, always takers, or never takers. Nonetheless, the research presented in this paper is significant in that it is the first to estimate the likelihood of belonging to any of these groups with respect to health policy analysis. It is with hope that the techniques described in this paper will inspire future research into causally explaining what motivates certain individuals to become compliers and encourage new approaches to determining whether their health care needs are being met.

Chapter 2

Laying Down the Welcome Mat: The Impact of the ACA Medicaid Expansion on Health Coverage for Previously Eligible Children

2.1 Introduction

Medicaid and the Children's Health Insurance Program (CHIP) have been essential pathways for providing insurance to low-income children. With the introduction of CHIP as part of the Balanced Budget Act of 1997, states received federal funds to cover children and pregnant women who were uninsured but had incomes exceeding the existing thresholds set for Medicaid. Currently, the program provides health coverage to nearly 6.8 million individuals each month, with the majority of which are children (CMS 2021). Over the last few decades, Medicaid and CHIP have helped to significantly reduce the number of uninsured children by more than 60% (Dubay and Kenney 2018); however, nearly 6 in 10 uninsured children are eligible but are not currently enrolled (Haley et al. 2021).

Part of the reduction in the number of uninsured children can be attributed to the establishment of the Affordable Care Act (ACA) in 2010 that brought upon the largest reform of the United States healthcare system since the introduction of Medicaid and Medicare in 1965 (Georgetown University Center for Children and Families 2017). Arguably, the most significant component was the state-elected expansion of Medicaid to low-income adults. The expansion has resulted in significant and greater reductions in the rates of the number of uninsured residing in states that expanded Medicaid, relative to states that elected not to participate in the expansion (Courtemanche et al. 2017; Decker et al. 2017 ; Kaestner et al. 2017; Miller and Wherry 2017; Simon et al. 2017; Sommers et al. 2015; Wherry and Miller 2016).[1]

While the ACA expanded Medicaid eligibility for both parents and childless adults, increases for children were limited because Medicaid and CHIP eligibility were already generous prior to the ACA's implementation. This was largely a result of the maintenance of eligibility (MOE) provision that prohibited states from restricting children's eligibility limits and enrollment procedures.[2] Therefore, many of the children who enrolled in Medicaid after the expansion did so while being already eligible Hudson and Moriya 2017). This phenomenon, dubbed the "welcome mat" effect, involves gains in public coverage among people who were already eligible for Medicaid and CHIP. (Frean et al. 2017; Hudson and Moriya 2017). The "welcome mat" effect could be explained by a number of factors unrelated to the change in Medicaid and CHIP eligibility thresholds for children. The ACA's outreach and enrollment strategies promoted affordable options in insurance programs, informed families about penalties for failing to meet insurance coverage mandates, and reduced administrative barriers to enrollment. Other features of the ACA that assisted in improving eligibility determination for Medicaid include, but are not limited to, the reduction or elimination of waiting periods; real-time eligibility determination; adopting uniform measures in counting income; and shifting to modernized, technology-driven approaches for enrollment and renewal procedures. These co-occurring characteristics may have increased Medicaid coverage for children, in spite of that this group was not the primary target of the ACA Medicaid expansion.

In this paper, I estimate the impact of the 2014 ACA Medicaid expansion on health coverage for children who were eligible for Medicaid and CHIP prior to the expansion. I utilize national-level data from the American Community Survey (ACS) from 2012 to 2017, and adopt a difference-in-differences strategy that measures the changes in children's eligibility for Medicaid and CHIP on children's health coverage before and after the ACA Medicaid expansion. I construct children's eligibility rates for Medicaid and CHIP using the state-

[1] These estimates range between 2 to 15 percentage points in the literature for low-income adults (Courtemanche et al. 2017; Duggan et al. 2019; Frean et al. 2017; Leung and Mas 2018; Simon et al. 2017; Wherry and Miller 2016).

[2] This no longer applies to children with incomes above 300% FPL as of October 2019.

age Modified Adjusted Gross Income (MAGI) thresholds available from the Kaiser Family Foundation (KFF).

I find a modest but statistically significant "welcome mat" effect ranging between 1.3 and 3.5 percentage points in public coverage for children who were previously eligible for Medicaid and CHIP. This is important given that a significant portion of my sample was already eligible for Medicaid and CHIP when states expanded Medicaid. Additionally, I find that there were significant increases in public coverage ranging between 1.8 and 7.9 percentage points for children who became eligible for Medicaid and CHIP after the expansion took place. Both sets of coefficients are robust with various specification checks, such as excluding states that expanded early and including controls for eligibility for premium subsidies in non-expansion states. When introducing a triple difference specification across states, time and expansion status, I find that increases for public coverage for both previous and newly eligible children are stronger in expansion states compared to non-expansion states. This potentially highlights the effectiveness in outreach and enrollment strategies in states that expanded Medicaid to adults.

I find significant evidence of crowd-out of private insurance, mainly employer sponsored insurance (ESI), for both the previously eligible and newly eligible children. This finding is interesting as one study that estimated the "welcome mat" effect for primarily adult populations found no evidence of crowding out (Frean et al. 2017). My findings are comparable to those from earlier studies that found crowd-out rates for low-income adults ranged from 23 to 33 percent as a result of the ACA expansion (Courtemanche et al., 2017; Kaestner et al., 2017). However, it is important to note that these estimates were statistically insignificant and, therefore, cannot be established as conclusive evidence of crowd-out. Given that much of the literature has found negligible effects of the ACA expansion on labor supply (Duggan et al., 2019; Garrett et al., 2017; Gooptu et al., 2016; Kaestner et al., 2017; Leung and Mas, 2018; Moriya et al., 2016), it is unlikely that crowd-out from employer sponsored insurance could likely be attributed to job leave. Instead, my findings could suggest that parents could prefer fully subsidized and comprehensive public coverage over limited and costly private coverage for their children.

Most studies that have examined the impacts of the ACA expansion on health coverage did not attempt to measure the "welcome mat" effect, as there are complexities associated with measuring income against Medicaid eligibility thresholds (Currie and Gruber 1996a; Currie and Gruber 1996b). Frean et al. (2017) measured the "welcome" effect concurrently with other ACA policy measures, such as the individual mandate and premium subsidies, for all individuals between zero and 64 years old. They found that the ACA led to significant decreases in the uninsured rate, with 29% of the decreases occurring among previously eligible individuals. However, they do not separately estimate the "welcome mat" effect for children, which is the main focus of this paper. Hudson and Moriya (2017) estimated the "welcome mat" effect for children, but utilized the parents' eligibility rates. They discovered evidence of the "welcome mat" impact among children whose parents had previously been eligible for Medicaid. However, parents' eligibility thresholds are much lower than those for children and, therefore, could understate the "welcome mat" effect for children. Furthermore, they excluded thresholds for separate CHIP and limited their sample to those below 138% FPL, both of which could significantly reduce the fraction of children eligible for Medicaid and CHIP. Lastly, they did not find any evidence of crowd-out for this population.

The paper proceeds as follows. Section 2.2 provides background on the provisions of the ACA and its effects on Medicaid and CHIP. Section 2.3 describes my data and eligibility measurements. Section 2.4 provides my empirical methodology. Section 2.5 presents my findings. Section 2.6 discusses the implications and interpretations of my results. Section 2.7 concludes.

2.2 Background

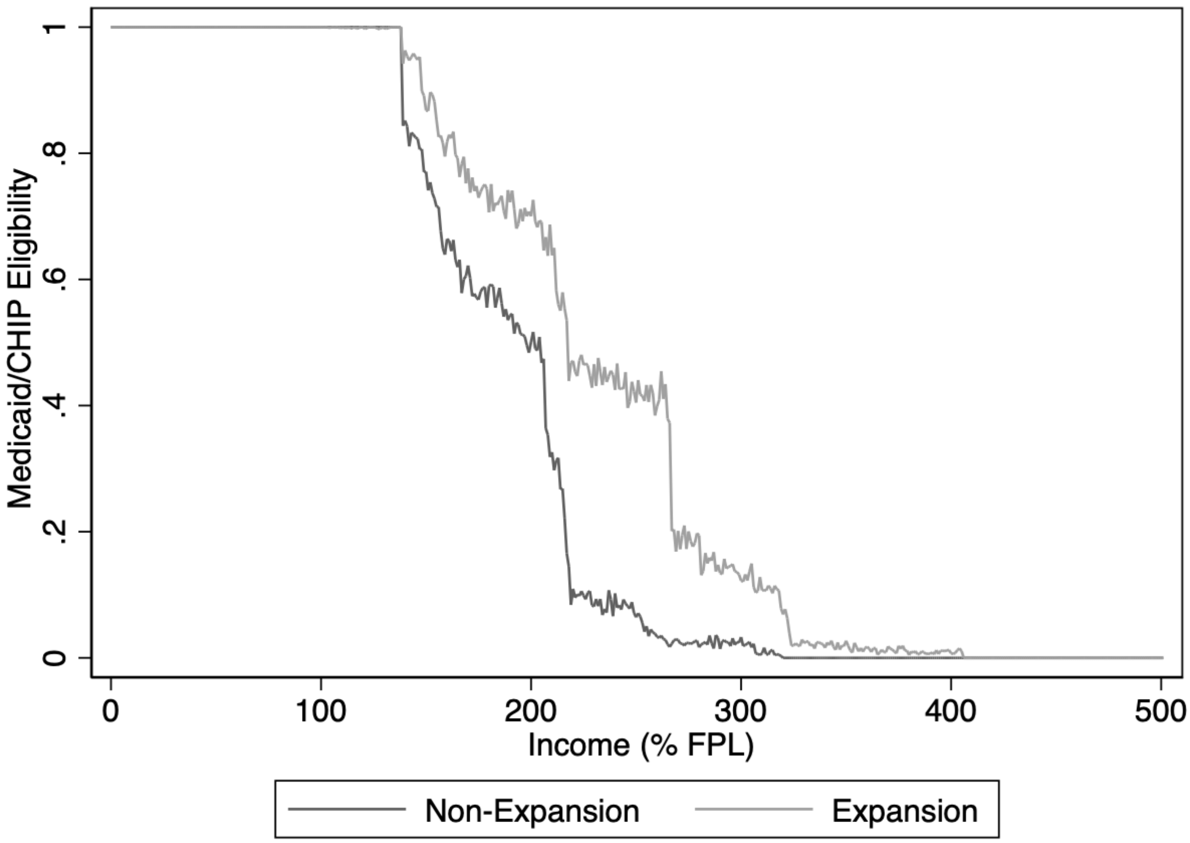
The Children's Health Insurance Program (CHIP) was introduced under the Balanced Budget Act of 1997 and serves as an essential source of health insurance for children, covering millions of children each month. CHIP is a federal-state partnership that provides health coverage to uninsured children in families with incomes too high to qualify for Medicaid but too low to afford private coverage. The financing model for CHIP includes enhanced federal support, where states receive federal matching funds based on the Medicaid formula for all children qualifying for CHIP (even if they are already covered by their Medicaid program). However, the degree of federal participation is greater than for Medicaid. Lastly, state governments can design their CHIP program in one of three ways: (1) a separate CHIP program, (2) through their Medicaid program, or (3) a combination of both.

Much of the growth in Medicaid and CHIP during recent years can be attributed to the policies introduced in the 2010 Affordable Care Act (ACA). The ACA was created for the purpose of achieving nearly universal coverage in the United States by introducing mandates, subsidizing premiums for private insurance purchases, expanding Medicaid, and reforming insurance markets and health insurance changes (Gruber 2011). Originally, the ACA proposed to expand Medicaid nationwide to all individuals with incomes below 138% of the federal poverty line (FPL), but was rejected by the Supreme Court in 2012.[3] However, in 2012, the Supreme Court ruled that states could voluntarily elect to participate in the expansion instead of being subjected to a mandate. Consequently, twenty-five states (including DC) adopted the Medicaid expansion on January 1st, 2014, with seven additional states following between 2014 and 2017. I map each state's expansion status from 2014–2017 in Figure B.1. This resulted in the average eligibility threshold rate for all childless adults in expansion states increasing from 30% FPL in 2013 to 138% in 2014. However, compared to adults, the eligibility thresholds for children were relatively robust before and after the expansion. Since 2014, the median income eligibility level for CHIP has been roughly 255% of the FPL (Brooks et al. 2021).[4] Furthermore, as illustrated in Figure 2.1, there are minor differences in children's eligibility status based on states' expansion status across income levels.

[3]The statutory cutoff for Medicaid eligibility in expansion states is 133% of the FPL, but the ACA requires states to apply a standard income disregard equivalent to 5% of the FPL, essentially raising the eligibility threshold to 138% of the FPL.

[4]The appendix provides several maps that summarize the changes in the eligibility thresholds before and after the expansion for several age groups and separate CHIP.

Figure 2.1: Mean Medicaid/CHIP Eligibility by Income (% FPL) 2012-2017: Ages 0-18



Note: Figure was created by author using information on states' Medicaid thresholds from the Kaiser Family Foundation (KFF).

In addition to expanding Medicaid, the ACA implemented an array of measures that could've potentially affected children's' enrollment into Medicaid and CHIP. First, the ACA redefined how financial eligibility is determined in Medicaid for non-disabled groups with the introduction of the Modified Adjusted Gross Income (MAGI) system. MAGI is calculated by applying various deductions to adjusted gross income (AGI). Moreover, the ACA required states to convert their eligibility criteria prior to its enactment to MAGI equivalent levels. This reduced the complexity in income-counting methods that were used prior to the ACA in determining eligibility across states (Brooks et al. 2021). The ACA also introduced the maintenance of effort (MOE) provision that required states to maintain Medicaid and CHIP income eligibility standards, preserve enrollment policies, and prohibit increases in premiums.[5] Together with the ACA Medicaid expansion, the MOE provision greatly re-

[5]This requirement was modified in 2018 under the Healthy Kids Act and only applies to families with

duced uninsured rates for children to their lowest points (Georgetown University Center for Children and Families 2017).

2.3 Data

I utilize the American Community Survey (ACS) as the primary data source in my study. The American Community Survey (ACS), which the United States Census Bureau conducts every month, is the largest household survey in the nation, surveying almost 3 million people annually, or over 92 percent of the country's population. The ACS includes information on health insurance coverage, measures of poverty and income, individual demographics, employment and geographic location. Since the ACS is mandatory, issues arising from sample selection are less likely to occur. The survey identifies all 50 states (including DC) along with localities, or Public Use Microdata Areas (PUMAs). PUMAS are made up of approximately 2300 mutually exclusive areas, each with at least 100,000 people. Given that the implementation of the ACA Medicaid occurred mainly in 2014, I would ideally sample the data from 2010 to 2017 to construct a balanced panel. As the PUMA boundaries were revised using the Decennial Census after 2011, I am, however, unable to use data gathered before 2012. Therefore, my study samples the ACS from 2012 to 2017.

Given my focus on children, I restrict my sample to those ages 18 and under with at least one biological parent present and living in the same household. I exclude married minors, children with Medicare coverage, and non-U.S. citizens.[6] The ACS also identifies household members by disability status (hearing difficulties, physical difficulties, etc.). Due to the complexities of determining eligibility for this population, I also exclude them from the analysis. One study that estimated the "welcome mat" effect for children limited their sample to families with incomes below 138% of the FPL (Hudson and Moriya 2017). However, imposing this restriction would eliminate those eligible for separate CHIP programs at higher income levels. Therefore, I do not impose any income restrictions in my sample.

The ACS asks each respondent if they are covered by any of the following categories of health insurance: Medicaid, Medicare, employer-sponsored, non-group private, TRICARE or other military health care, Medical Assistance, government assistance programs for low-

incomes of less than 300% of the FPL.

[6]Non-US citizens are ineligible for Medicaid unless they meet the requirement of waiting at least 5 years to receive "qualified" immigration status before becoming eligible. Exemptions exist for some groups (refugees, asylees, and lawfully permanent residents who were formally refugees or asylees).

income or disabled individuals, or any unspecified. This allowed me to categorize health coverage into the following types: public (Medicaid), employer sponsored, non-group private, or uninsured, which serve as the variables of interest in this study. Although the Census uses the ACS as a reliable source to determine how many Americans have health insurance, it does have its limitations for determining Medicaid eligibility because it only asks respondents if they have ever received "Medicaid, Medical Assistance, or any type of government-assistance plan for low-income individuals or individuals with disabilities." This presents a potential issue, as respondents may misreport private coverage as public coverage and vice versa.[7]

I divide Medicaid and CHIP-eligible children into two mutually exclusive groups: those who were "previously eligible" and those who were "newly eligible". The first group is comprised of children who were eligible for Medicaid and CHIP prior to the 2014 ACA expansion. These children define the "welcome mat" population that may have enrolled due to reductions in administrative barriers, the individual mandate, outreach efforts and other provisions under the ACA (Aizer 2007). Identifying the take-up of Medicaid and CHIP is important for this population given that the income-related eligibility requirements for Medicaid and CHIP were relatively robust between 2012 and 2017. Therefore, any increases observed for this group would reflect the effectiveness of the policies or actions under the ACA that were unrelated to expanding income generosity in existing state programs. The newly eligible population represents children who became eligible under the new Medicaid and CHIP income thresholds set by the state after the 2014 ACA Medicaid expansion took place.

To measure eligibility status, I use ratios of family income to poverty thresholds for households provided in the ACS. The ACS calculates poverty status as a ratio of family income to the poverty threshold set based on family size and the number of related children under 18.[8] For example, the poverty threshold in 2015 for a 3-person family with one child under 18 was $19,708. Suppose the family's income for that year was $40,000. The family's poverty level is thus calculated to be roughly 2.03 or 203 percent above the federal poverty line (FPL). The thresholds are provided by the Current Population Survey (CPS), vary across years, and are set separately for Alaska and Hawaiʻi.

The Medicaid eligibility rates were constructed based on a set of MAGI-converted thresholds based on state, PUMA and age obtained by the Centers for Medicare and Medi-

[7] Mach and O'Hara (2011) found that the ACS typically overestimates non-group private coverage compared to other data sources.

[8] Measures not considered when calculating family income include non-cash benefits (e.g. food stamps and housing subsidies), capital gains or losses, and tax credits.

caid Services (CMS) and the Kaiser Family Foundation (KFF). I standardize the eligibility determinations using the 2013 state MAGI-converted thresholds for age group and separate CHIP.[9] I define a child in a given age group and state to be previously eligible for Medicaid and CHIP if their family income, measured as a percentage of the FPL, is below the state-age MAGI-converted threshold set before the 2014 ACA Medicaid expansion. Similarly, I define a child to be newly eligible for Medicaid and CHIP if their family income, reported in the ACS and measured as a percentage of the FPL, is below the state-age MAGI-converted threshold set in either 2014, 2015, 2016 or 2017, but above the thresholds set prior to the expansion.[10][11]

2.3.1 Summary Statistics

Table 2.1 presents the summary statistics of the mutually exclusive eligibility measures and stratified by race and ethnicity. The sample statistics are weighted using ACS weights. Approximately 42% of children were eligible for Medicaid and CHIP prior to the expansion, with rates decreasing over time. This represents a growth in family income as most states either maintained or increased their MAGI-converted threshold limits. Following the expansion, approximately 9.6-10.2% of children became eligible for Medicaid and CHIP, depending on the year.[12] White children were significantly less likely than other racial/ethnic groups to be eligible for Medicaid and CHIP both before and after the expansion.

Table 2.2 shows the time trends in health coverage by race and ethnicity from 2012 to 2017. Public coverage grew steadily at a net increase of 2.2% in 2016, but fell in 2017. Up

[9] I applied the ACA's statutory 5% income disregard to all MAGI-converted thresholds. As a robustness check, I standardized the thresholds using 2012 state MAGI-converted thresholds and found this to have negligible impact on my results.

[10] There are very few instances where a state's MAGI-converted threshold after the expansion becomes less generous than what it set prior to the expansion. An example of this is Arkansas, where the threshold for children ages 6-18 in 2016 was 147%, but 200% in 2013. As a robustness check, I omitted states where this occurs and found that this had little to no impact on my results.

[11] There are a few limitations concerning eligibility that are worth noting. First, one study argued that the income distribution across state-areas may be related to private insurance premiums, Medicaid expansion, and unobserved factors correlated with family income and preferences for insurance (Frean et al. 2017). Furthermore, they stated that the mapping of income reported by the ACS onto ACS-related eligibility is imprecise and biased toward the null. They addressed these issues by using a simulated measure of eligibility proposed in Currie and Gruber (1996a) and Currie and Gruber (1996b) as an instrument for Medicaid eligibility. Their results did not significantly differ from what was reported as the main result. Therefore, this provides some reassurance as this study adopts an empirical framework similar to theirs.

[12] In figures B.2, B.3, B.4 and B.5 of the appendix, I map out the changes in MAGI thresholds rates by state, age group, and program from 2013 to 2017.

Table 2.1: Time Trends of Medicaid and CHIP Eligibility Variables 2012-2017

	2012		2013		2014		2015		2016		2017	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
All												
Previously Eligible	41.8%	(49.3%)	41.5%	(49.3%)	41.1%	(49.2%)	39.8%	(49.0%)	38.5%	(48.6%)	37.1%	(48.3%)
Newly Eligible	-	-	-	-	9.6%	(29.5%)	9.8%	(29.7%)	10.1%	(30.1%)	10.2%	(30.2%)
White												
Previously Eligible	32.7%	(46.9%)	32.2%	(46.7%)	31.6%	(46.5%)	30.6%	(46.1%)	29.0%	(45.4%)	28.0%	(44.9%)
Newly Eligible	-	-	-	-	6.7%	(25.0%)	6.5%	(24.7%)	6.8%	(25.3%)	6.9%	(25.3%)
Black												
Previously Eligible	62.3%	(48.5%)	62.3%	(48.5%)	62.1%	(48.5%)	60.4%	(48.9%)	58.5%	(49.3%)	56.6%	(49.6%)
Newly Eligible	-	-	-	-	8.9%	(28.5%)	9.5%	(29.3%)	9.7%	(29.6%)	10.6%	(30.8%)
Hispanic												
Previously Eligible	54.3%	(49.8%)	53.9%	(49.8%)	53.6%	(49.9%)	51.9%	(50.0%)	50.7%	(50.0%)	48.5%	(50.0%)
Newly Eligible	-	-	-	-	17.1%	(37.6%)	17.7%	(38.2%)	17.8%	(38.3%)	17.7%	(38.1%)

Notes: Table presents weighted means, with standard deviations in parentheses, for children ages 0-18 years old with a biological mother present. Data is sourced from the ACS for the years 2012-2017. All eligibility variables are constructed by comparing income-to-poverty thresholds from the ACS to MAGI-converted thresholds available by state-year and taken directly from the Kaiser Family Foundation and Medicaid.gov. The measure "Previously Eligible" was constructed based on 2013 state eligibility criteria.

to 2016, gains in public coverage for Black and Hispanic children outpaced those for White children, with the former facing greater losses in 2017. Across race and ethnicity, declines in uninsured rates were greatest for Hispanic children (3.9%) and fewer for Black children (1.4%), and White children (1.2%). In aggregate, there were net decreases in uninsured rates of 1% in 2014, 2.1% in 2015, 2.4% in 2016, and 2.1% in 2017, compared to the 2012-2013 period. In 2017, there were trends of declining public insurance and rising uninsurance rates. This pattern is consistent with a previous report that documented the increases in the uninsured rate for children starting in 2017 (Alker and Corcoran, 2020).

Table 2.2: Time Trends of Health Insurance Variables 2012-2017

	2012		2013		2014		2015		2016		2017	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
All												
Public Coverage	32.5%	(46.9%)	32.8%	(46.9%)	33.6%	(47.2%)	34.8%	(47.6%)	34.8%	(47.6%)	34.3%	(47.5%)
Employed Sponsored	56.5%	(49.6%)	55.9%	(49.6%)	56.1%	(49.6%)	55.8%	(49.7%)	56.2%	(49.6%)	57.0%	(49.5%)
Non-Group Private	7.6%	(26.5%)	7.0%	(25.5%)	7.2%	(25.9%)	7.7%	(26.6%)	7.7%	(26.7%)	7.3%	(26.0%)
Uninsured	6.2%	(24.1%)	6.4%	(24.4%)	5.3%	(22.3%)	4.2%	(20.1%)	3.9%	(19.4%)	4.2%	(20.0%)
White												
Public Coverage	20.4%	(40.3%)	20.5%	(40.4%)	21.1%	(40.8%)	22.1%	(41.5%)	22.1%	(41.5%)	21.7%	(41.2%)
Employed Sponsored	68.4%	(46.5%)	67.8%	(46.7%)	68.0%	(46.6%)	67.6%	(46.8%)	67.9%	(46.7%)	68.8%	(46.3%)
Non-Group Private	9.2%	(28.8%)	8.6%	(28.2%)	8.7%	(28.2%)	9.1%	(28.8%)	9.2%	(28.9%)	8.4%	(27.7%)
Uninsured	4.8%	(21.4%)	5.1%	(21.9%)	4.3%	(20.4%)	3.6%	(18.7%)	3.3%	(17.9%)	3.6%	(18.6%)
Black												
Public Coverage	52.4%	(49.9%)	52.7%	(49.9%)	54.2%	(49.8%)	54.6%	(49.8%)	54.2%	(49.8%)	53.0%	(49.9%)
Employed Sponsored	40.5%	(49.1%)	40.0%	(49.0%)	39.2%	(48.8%)	39.7%	(48.9%)	40.7%	(49.1%)	42.1%	(49.4%)
Non-Group Private	4.7%	(21.1%)	4.1%	(19.9%)	4.3%	(20.3%)	4.7%	(21.3%)	5.0%	(21.8%)	4.7%	(21.2%)
Uninsured	5.4%	(22.7%)	5.5%	(22.8%)	4.4%	(20.5%)	3.6%	(18.7%)	3.0%	(17.2%)	3.6%	(18.6%)
Hispanic												
Public Coverage	52.3%	(49.9%)	52.7%	(49.9%)	52.9%	(49.9%)	55.2%	(49.7%)	55.0%	(49.8%)	53.9%	(49.9%)
Employed Sponsored	35.8%	(47.9%)	35.2%	(47.8%)	36.5%	(48.1%)	35.9%	(48.0%)	36.6%	(48.2)	37.6%	(48.4%)
Non-Group Private	5.0%	(21.7%)	4.2%	(20.0%)	4.8%	(21.3%)	5.3%	(22.4%)	5.3%	(22.4%)	5.6%	(22.9%)
Uninsured	10.0%	(30.0%)	9.9%	(29.9%)	8.1%	(27.2%)	6.1%	(23.9%)	6.0%	(23.7%)	6.1%	(23.9%)

Notes: Table presents weighted means, with standard deviations in parentheses, for children ages 0-18 years old with at least one biological parent present. Data is sourced from the ACS for the years 2012-2017.

2.4 Empirical Methodology

I adopt a difference in differences (DD) framework similar to Frean et al. (2017) that leverages the repeated cross-sectional design of the ACS. I estimate changes in health insurance coverage that resulted from changes in Medicaid and CHIP eligibility under the ACA Medicaid expansion. Given that the policies under the ACA may have evolved over time, I use 2012-2013 as the pre-ACA baseline period and estimate the policy effects separately for 2014, 2015, 2016, and 2017. I estimate the following model:

$$\begin{aligned}
Y_{iat} = {} & \beta_0 + \beta_1 PreviouslyEligible_{ia} \\
& + \beta_2 NewlyEligible2014_{ia} + \beta_3 NewlyEligible2015_{ia} \\
& + \beta_4 NewlyEligible2016_{ia} + \beta_5 NewlyEligible2017_{ia} \\
& + \beta_6 PreviouslyEligible_{ia} * \theta_{2014} + \beta_7 PreviouslyEligible_{ia} * \theta_{2015} \\
& + \beta_8 PreviouslyEligible_{ia} * \theta_{2016} + \beta_9 PreviouslyEligible_{ia} * \theta_{2017} \\
& + \beta_{10} NewlyEligible2014_{ia} * \theta_{2014} + \beta_{11} NewlyEligible2015_{ia} * \theta_{2015} \\
& + \beta_{12} NewlyEligible2016_{ia} * \theta_{2016} + \beta_{13} NewlyEligible2017_{ia} * \theta_{2017} \\
& + \beta_x X_{iat} + \theta_t + \gamma_a + unemployment_{it} + \epsilon_{iat}
\end{aligned} \tag{1}$$

where Y_{iat} is a binary indicator for either: Medicaid and CHIP, employer sponsored, non-group private, or no health coverage. The term $PreviouslyEligible_{ia}$ equals to 1 if child i observed in year t was eligible for Medicaid and CHIP under the 2013 age-year MAGI-converted thresholds set in PUMA a, and 0 otherwise. There are four eligibility parameters that indicate whether child i was newly eligible for Medicaid and CHIP under the age-year MAGI-converted thresholds set in PUMA a in year t. The term $NewlyEligible2014_{ia}$ equals 1 if child i observed in year t was eligible for Medicaid and CHIP under the 2014 age-year MAGI-converted thresholds set in PUMA a, but ineligible according to the 2013 MAGI-converted thresholds, and 0 otherwise. I define the remaining parameters for 2015 to 2017 in the same fashion. The coefficients β_1 through β_5 capture the policy parameters' baseline or pre-ACA effects. Each of the policy parameters is interacted with a post-ACA year fixed effect and captures the policy impacts of the ACA Medicaid expansion on health coverage for each year after the expansion took place. Therefore, β_6 through β_{13} serves as the main coefficients of interest.

The term X_{ijt} is a vector containing demographic characteristics of the mother: age, educational attainment, work status, marital status, disability status, number of children, and the child: gender, income group, age, and race and ethnicity.[13] I also include indicators for whether the child's father is present and control for the father's work status. I include

[13] I stratified the income into the following groups: 0-50% FPL, 50-100% FPL, 100-138% FPL, 138-200% FPL, 200-250% FPL, 250-300% FPL, 300-350% FPL, 350-400% FPL, 400-450% FPL, 450-500% FPL, and greater than 500% FPL.

year, θ_t, and PUMA, γ_a, fixed effects into the regression. Additionally, I adjust the model using annual county-level unemployment rates directly from the Bureau of Labor Statistics. I denote ϵ_{iat} as a random error term. All standards errors are clustered at the PUMA-level to account to serial correlation (Bertrand et al., 2004).

2.5 Results

2.5.1 Estimating the Welcome Mat Effect

In Table 2.3, I estimate the difference-in-differences model outlined in equation (1) to measure the effects of the ACA's increases in Medicaid and CHIP eligibility on various categories of health coverage for children. The summary statistics for the demographic controls can be found in Table (B.1) of the appendix. The results reveal a significant positive relationship between public coverage and all eligibility measures. The coefficients show that the ACA expansion led to both modest and significant increases of roughly 1.3 (2014), 2.6 (2015), 3.1 (2016), and 3.5 (2017) percentage points in public coverage for children who were eligible for Medicaid and CHIP prior to the expansion. This provides evidence of a "welcome mat" effect that is steadily increasing over time, with the effect doubling from 2014 to 2015, but flattening in 2017. This suggests that non-income related features of the ACA may have been effective in driving the "welcome mat" effect.

Table 2.3: Difference-in-Differences Results of the Effects of ACA Expansion on Health Coverage for Children

	(1) Public	(2) ESI	(3) Non-Group	(4) Uninsured
Medicaid Eligibility (Previous)				
Previously Eligible 2014 * Yr 2014	0.013***	-0.004	0.004**	-0.010***
	(0.002)	(0.003)	(0.002)	(0.001)
Previously Eligible 2015 * Yr 2015	0.026***	-0.008***	0.003*	-0.016***
	(0.002)	(0.003)	(0.002)	(0.001)
Previously Eligible 2016 * Yr 2016	0.031***	-0.009***	0.003	-0.021***
	(0.002)	(0.003)	(0.002)	(0.001)
Previously Eligible 2017 * Yr 2017	0.035***	-0.016***	0.007***	-0.020***
	(0.003)	(0.003)	(0.002)	(0.002)
Medicaid Eligibility (New)				
Newly Eligible 2014 * Yr 2014	0.018***	-0.001	-0.001	-0.017***
	(0.005)	(0.005)	(0.003)	(0.003)
Newly Eligible 2015 * Yr 2015	0.052***	-0.016***	-0.001	-0.037***
	(0.005)	(0.005)	(0.003)	(0.003)
Newly Eligible 2016 * Yr 2016	0.079***	-0.029***	-0.005**	-0.039***
	(0.005)	(0.005)	(0.002)	(0.003)
Newly Eligible 2017 * Yr 2017	0.073***	-0.029***	0.001	-0.040***
	(0.005)	(0.005)	(0.003)	(0.003)
Policy Controls				
Previously Eligible	0.022***	-0.018***	-0.004**	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Newly Eligible 2014	0.010	-0.036**	0.013	0.006
	(0.018)	(0.017)	(0.009)	(0.007)
Newly Eligible 2015	0.033*	-0.024	-0.012	0.009
	(0.019)	(0.018)	(0.009)	(0.008)
Newly Eligible 2016	-0.044	0.066*	0.038*	-0.065**
	(0.035)	(0.040)	(0.021)	(0.027)
Newly Eligible 2017	0.012	-0.027	-0.042**	0.066**
	(0.034)	(0.039)	(0.021)	(0.027)
Observations	3,248,152	3,248,152	3,248,152	3,248,152

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors in parentheses and clustered at the PUMA level.The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

My results exhibit trends similar to Frean et al. (2017), but at a smaller magnitude, with the authors modeling for all individuals between 0-64 years old and including multiple policy variables such as coverage mandates and private insurance subsidies. Additionally, Hudson and Moriya (2017) found that the "welcome mat" effect was decreasing over time, where the opposite occurs in my findings. This demonstrates that modeling children's eligibility after those for parents presents a new perspective on the "welcome mat" effects of children's enrollment in Medicaid.[14] The next set of coefficients measures the impact on health coverage of children who became eligible for Medicaid and CHIP under the ACA expansion. The coefficients show that the ACA expansion led to statistically significant increases of roughly 1.8 (2014), 5.2 (2015), 7.9 (2016), and 7.3 (2017) percentage points in public coverage for children who became newly eligible for Medicaid and CHIP after 2014. These patterns are consistent with Table 2.2, where public coverage increased between 2014 to 2016, but decreased in 2017.

Using the eligibility means from Table 2.1 and the coefficients from Table 2.3, I estimate that in 2014, the ACA Medicaid expansion to the portion of those eligible prior to the expansion (41.1%) led to an increase in public coverage of 0.54 percentage points.[15] The effects of the expansion to the newly eligible population (8.1%) led to an increase of 0.17 percentage points in public coverage. These amounts sum to a 0.71 percentage increase in public coverage in 2014. The total increases in public coverage sum up to 1.55 percentage points in 2015, 2.0 percentage points in 2016, and 2.05 percentage points in 2017. In 2014, 76 percent of the public coverage gains may be attributed to the "welcome mat," compared to 67 percent in 2015, 60 percent in 2016, and 63 percent in 2017. These estimates suggest that the increasing enrollment of children in Medicaid and CHIP following the ACA Medicaid expansion was mostly credited to the "welcome mat" effect, even as more children acquired eligibility for the programs.

Starting in 2015, I observed small but significant estimates of crowd-out in employer sponsored insurance for both the previously eligible and newly eligible population. My estimates are comparable in size to a previous study that estimated private crowd-out resulting from Medicaid expansions for children and pregnant women in the 1990s (Cutler and Gruber (1996)). This is an important finding as it presents new evidence of private insurance

[14] It is important to note the authors restricted their sample to children whose family incomes were below 138% of the FPL and did not model for CHIP. This approach is infeasible in my analysis as the MAGI-converted income thresholds for children are well above 138%, preventing me from differentiating between those who were previously eligible and newly eligible for Medicaid and CHIP.

[15] This is derived by multiplying the percentage of the previously eligible population in 2014 in Table 2.1 with its corresponding coefficient from Table 2.3, i.e., 0.013 * 41.1 = 0.54.

crowd-out introduced in the ACA and has not been conclusively established in the literature for children. Sommers et al. (2015) leveraged the variation of early expansions across counties in California and found no evidence of crowd-out among already eligible children. However, their sample was limited to 2014, when crowd-out only occurred in 2015 in my results. Frean et al. (2017) found no crowd-out in their results when leveraging the variation in MAGI thresholds across households and age groups. However, it is important to note that the authors incorporated other policy elements of the ACA into their analysis, such as subsidies for non-group private insurance and tax penalties under the individual mandate. Additionally, they did not extend their sample past 2015 or restrict their analysis exclusively to children. Hamersma et al. (2019) modeled children's eligibility after that for parents and found some evidence of crowd-out, but only for some persistently disadvantaged subgroups. Other studies have documented some degree of crowd-out in private insurance but used states' expansion status instead of MAGI thresholds as a proxy for eligibility into Medicaid and did not limit their focus to children (Courtemanche et al., 2017; Kaestner et al., 2017 and Duggan et al., 2019). Most importantly, only Duggan et al. (2019) found statistically significantly effects. Therefore, the main contribution of my results not only establishes evidence of crowd-out of private insurance for children, but it also adds to the limited findings that were documented in the context of the ACA Medicaid expansion.

My findings for private insurance support a 2013 report that predicted enrollment in employer-sponsored insurance would decrease as a result of the ACA (Gallen and Mulligan 2013). However, it is uncertain whether the crowding out of employer-sponsored insurance can be attributed to job leave. Past literature has been inconclusive in finding any causal effects of the ACA Medicaid expansion on labor supply (Duggan et al., 2019; Garrett et al., 2017; Gooptu et al., 2016; Kaestner et al., 2017; Leung and Mas, 2018; Moriya et al., 2016). Other studies found that in response to employer mandates, some employers opted out of providing health insurance to part-time workers, forcing employees to obtain coverage through other means (Batkins et al. 2014 and Mulligan 2020). My findings could suggest that parents, especially in low-income households, may prefer fully subsidized and comprehensive public coverage for their children over restrictive and costly private coverage. This is plausible given the significant costs parents‘ incur when investing in their children's health care.[16] However, more research in this area is needed because this paper makes no attempt to support this argument.

[16]According to a 2015 report from the United States Department of Agriculture, roughly 9% of expenses for children between ages 0 and 17 went to health care (Lino et al. 2017). Additionally, the report found that the average cost of raising a child from birth to age 17 was $233,610 (in 2015 dollars).

2.5.2 Heterogeneous Effects by Race and Ethnicity

Seeing that several studies have documented racial and ethnic disparities in acquiring public coverage, I estimate equation (1) by race and ethnicity and report my results in Table 2.4[17]. Overall there was a strong "welcome mat" effect for White children as public coverage increased by 1.7 to 5.3 percentage points, depending on the year. The "welcome mat" effect Black children was insignificant and close to zero, suggesting that Black children were more likely than White children to have already been enrolled in Medicaid prior to the expansion. This is consistent with Table 2.2 showing that public coverage is significantly higher for Black children compared to White children. An alternative explanation is that that the poverty rate for Black households is nearly three times higher than the poverty rate observed for White households (DeNavas-Walt et al., 2013), making it easier for Black children to enroll prior to the expansion. I observed a small but significant "welcome mat" effect in public coverage for Hispanic children, but only for 2015. This supports previous studies have cited barriers relating to fear, confusion, and language related to the process of applying for health coverage and disproportionately affecting the Hispanic population (Stuber et al., 2000) and (Kaiser Family Foundation, 2021).

[17]For a more extensive review of the literature, see Medicaid and CHIP Payment and Access Commission (MACPAC) (2021).

Table 2.4: Difference-in-Differences Results of the Effects of ACA Expansion on Health Coverage for Children by Race/Ethnicity

	White				Black				Hispanic			
	Public	ESI	Non-Group	Uninsured	Public	ESI	Non-Group	Uninsured	Public	ESI	Non-Group	Uninsured
Medicaid Eligibility (Previous)												
Previously Eligible 2014 * Yr 2014	0.016***	-0.006*	0.003		0.003	0.006	0.006	-0.006	0.007	-0.003	0.002	-0.006
	(0.003)	(0.004)	(0.002)	(0.002)	(0.006)	(0.007)	(0.004)	(0.004)	(0.006)	(0.006)	(0.003)	(0.004)
Previously Eligible 2015 * Yr 2015	0.037***	-0.016***	0.004*	-0.017***	-0.001	0.012	0.000	-0.006	0.015***	-0.006	-0.003	-0.007**
	(0.003)	(0.004)	(0.002)	(0.002)	(0.007)	(0.008)	(0.004)	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)
Previously Eligible 2016 * Yr 2016	0.047***	-0.023***	0.001	-0.022***	-0.003	0.019**	-0.000	-0.012***	0.009	0.001	0.001	-0.012***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.007)	(0.008)	(0.004)	(0.003)	(0.006)	(0.006)	(0.004)	(0.004)
Previously Eligible 2017 * Yr 2017	0.050***	-0.029***	0.005**	-0.020***	-0.001	0.008	0.006	-0.007**	0.009	0.001	0.004	-0.013***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.007)	(0.008)	(0.004)	(0.004)	(0.006)	(0.006)	(0.004)	(0.004)
Medicaid Eligibility (New)												
Newly Eligible 2014 * Yr 2014	0.015**	0.001	-0.001	-0.012***	0.029**	-0.001	-0.000	-0.020***	0.014*	-0.004	-0.002	-0.016***
	(0.007)	(0.007)	(0.005)	(0.004)	(0.014)	(0.014)	(0.007)	(0.007)	(0.008)	(0.009)	(0.004)	(0.006)
Newly Eligible 2015 * Yr 2015	0.039***	-0.013*	0.001	-0.023***	0.037**	-0.014	0.003	-0.027***	0.055***	-0.017**	-0.008*	-0.037***
	(0.007)	(0.007)	(0.005)	(0.004)	(0.014)	(0.014)	(0.007)	(0.007)	(0.008)	(0.009)	(0.004)	(0.005)
Newly Eligible 2016 * Yr 2016	0.073***	-0.032***	-0.001	-0.025***	0.061***	-0.025*	-0.010*	-0.034***	0.071***	-0.025***	-0.007	-0.037***
	(0.007)	(0.007)	(0.004)	(0.004)	(0.013)	(0.013)	(0.006)	(0.006)	(0.008)	(0.008)	(0.004)	(0.005)
Newly Eligible 2017 * Yr 2017	0.064***	-0.028***	0.001	-0.027***	0.035**	-0.011	0.003	-0.024***	0.069***	-0.025***	-0.003	-0.044***
	(0.007)	(0.007)	(0.004)	(0.004)	(0.014)	(0.013)	(0.006)	(0.007)	(0.009)	(0.009)	(0.004)	(0.005)
Policy Controls												
Previously Eligible	0.015***	-0.014***	-0.004*	0.003*	0.026***	-0.026***	-0.009**	0.005	0.046***	-0.029***	-0.003	-0.008**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.007)	(0.008)	(0.004)	(0.004)	(0.006)	(0.006)	(0.003)	(0.004)
Newly Eligible 2014	-0.002	-0.036*	0.009	0.010	-0.008	0.067	0.001	0.008	-0.022	-0.028	0.029	0.004
	(0.021)	(0.020)	(0.012)	(0.006)	(0.042)	(0.070)	(0.027)	(0.013)	(0.039)	(0.038)	(0.023)	(0.025)
Newly Eligible 2015	0.028	-0.007	-0.006	0.002	0.068	-0.136*	0.007	-0.007	0.006	0.017	-0.021	0.019
	(0.023)	(0.021)	(0.012)	(0.007)	(0.044)	(0.071)	(0.027)	(0.015)	(0.045)	(0.044)	(0.022)	(0.026)
Newly Eligible 2016	-0.026	0.049	0.067*	-0.087**	-0.111	0.228	-0.057	-0.100	-0.008	0.033	0.010	-0.047
	(0.043)	(0.057)	(0.036)	(0.034)	(0.121)	(0.140)	(0.075)	(0.096)	(0.065)	(0.068)	(0.033)	(0.052)
Newly Eligible 2017	0.012	-0.025	-0.070**	0.084**	0.050	-0.173	0.044	0.121	0.042	-0.042	-0.018	0.032
	(0.041)	(0.057)	(0.035)	(0.033)	(0.120)	(0.140)	(0.075)	(0.096)	(0.061)	(0.065)	(0.033)	(0.052)
Observations	1,976,144	1,976,144	1,976,144	1,976,144	362,743	362,743	362,743	362,743	632,904	632,904	632,904	632,904

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors in parentheses and clustered at the PUMA level.The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

Of those who were previously eligible for Medicaid/CHIP, White children exhibited statistically significant crowding out in private insurance in 2016 and 2017, while Black and Hispanic children displayed minimal and statistically insignificant impacts. Among children who became newly eligible for Medicaid/CHIP after the expansion, gains in public coverage for Black and Hispanic children exceeded those for White children in 2014 and 2015. However, this pattern reverses starting in 2016. This is consistent with the health coverage trends outlined in Table 2.2, where public coverage gains were greatest for Hispanic and Black children from 2012 to 2015, but then experienced greater decreases relative to White children. However, although public coverage gains amongst the newly eligible population were strong for White children, the net losses in uninsured rate were significant and stronger for Black and Hispanic children, providing evidence that the ACA did assist in reducing racial disparities in health coverage for newly eligible children.

2.5.3 Welcome Mat Effects by State Expansion Status

Figure 2.5 demonstrates that across a range of income levels, children were generally more eligible for Medicaid and CHIP in expansion states than in non-expansion states. It is possible that efforts in outreach and the implementation of enrollment strategies were more effectively made in states that participated in the Medicaid expansion versus states that did not. This would spur greater increases in public coverage among previously eligible children, thus resulting in higher incidences of the "welcome mat" effect. Additionally, it is possible that parents could be indcued to enroll their children into Medicaid and CHIP once they themselves became eligible from the ACA expansion that effective in expansion states. To test this, I employ a triple difference model that exploits the variation across eligibility status, year, and states' expansion status on health coverage. I estimate the following model:

$$\begin{gathered}
Y_{iat} = \beta_0 + \beta_1 Expand_{ia} + \beta_2 PreviouslyEligible_{ia} \\
+\beta_3 NewlyEligible2014_{ia} + \beta_4 NewlyEligible2015_{ia} \\
+\beta_5 NewlyEligible2016_{ia} + \beta_6 NewlyEligible2017_{ia} \\
+\beta_7 PreviouslyEligible_{ia} * Expand_{ia} \\
+\beta_8 NewlyEligible2014_{ia} * Expand_{ia} + \beta_9 NewlyEligible2015_{ia} * Expand_{ia} \\
+\beta_{10} NewlyEligible2016_{ia} * Expand_{ia} + \beta_{11} NewlyEligible2017_{ia} * Expand_{ia} \\
+\beta_{12} PreviouslyEligible_{ia} * \theta_{2014} + \beta_{13} PreviouslyEligible_{ia} * \theta_{2015} \\
+\beta_{14} PreviouslyEligible_{ia} * \theta_{2016} + \beta_{15} PreviouslyEligible_{ia} * \theta_{2017} \\
+\beta_{16} NewlyEligible2014_{ia} * \theta_{2014} + \beta_{17} NewlyEligible2015_{ia} * \theta_{2015} \\
+\beta_{18} NewlyEligible2016_{ia} * \theta_{2016} + \beta_{19} NewlyEligible2017_{ia} * \theta_{2017} \\
+\beta_{20} PreviouslyEligible_{ia} * \theta_{2014} * Expand_{ia} + \beta_{21} PreviouslyEligible_{ia} * \theta_{2015} * Expand_{ia} \\
+\beta_{22} PreviouslyEligible_{ia} * \theta_{2016} * Expand_{ia} + \beta_{23} PreviouslyEligible_{ia} * \theta_{2017} * Expand_{ia} \\
+\beta_{24} NewlyEligible2014_{ia} * \theta_{2014} * Expand_{ia} + \beta_{25} NewlyEligible2015_{ia} * \theta_{2015} * Expand_{ia} \\
+\beta_{26} NewlyEligible2016_{ia} * \theta_{2016} * Expand_{ia} + \beta_{27} NewlyEligible2017_{ia} * \theta_{2017} * Expand_{ia} \\
+\beta_x X_{iat} + \theta_t + \gamma_a + unemploymentit + \epsilon_{iat}
\end{gathered} \tag{4}$$

where $Expand_{ia}$ is a treatment variable that equals 1 if individual i resided in a state containing PUMA a that expanded Medicaid at time t, and 0 otherwise. As some states expanded later in the year or in succeeding years, this term is activated the year after it was adopted. Therefore, $Expand_{ia}$ reflects the variation in the timing of states' decisions to expand Medicaid eligibility. I define a state to have expanded in the current year if they have done so on or prior to July 1st[18]

In Table 2.5, I observe that for all years, the "welcome mat" effect is more pronounced in expansion states than in non-expansion states. From 2015 to 2017, I observe significant and positive increases in public coverage for the newly eligible population in expansion states compared to non-expansion states. This demonstrates that while Medicaid enrollment was somewhat delayed in the first year of the ACA's Medicaid expansion, the policies under the ACA were more successful at enrolling children in Medicaid who had previously been eligible and who resided expansion states.

I find significant crowding-out in ESI coverage for expansion states vs. non-expansion states in the previous eligible population. However, in the same population, changes in the uninsured rate are small and insignificant, except in 2014, where the estimate is negligible. These estimates suggests that rather than acquiring brand new coverage, parents are dropping private insurance in favor of Medicaid for their children. This supports the notion that parents prefer fully subsidized public insurance over costly private insurance for their children, as it would considerably help families with lower incomes. Lastly, I find significant decreases in non-group private insurance for new eligible children by state expansion status. However, this result is bolstered by the fact that residents of non-expansion states were given access to subsidies for private insurance purchased in the ACA Marketplace. Therefore, I do not attribute this effect as crowding-out.

2.6 Robustness Checks

2.6.1 Early Expansion States

Before the ACA Medicaid expansion was implemented, there were six states (CA, CT, DC, MN, NJ, and WA) that expanded public coverage prior to 2014, between 2011 and 2013. The early expansion of Medicaid in these states was mainly targeted towards low-income childless adults and parents, but had little to no impact on children's MAGI-converted thresholds. However, it is possible that parents who qualified for Medicaid prior to the expansion may have been motivated to enroll their children as well. In the literature, it

[18]There are 6 states: AK, IN, LA, MT, NH and PA that expanded Medicaid after July 1st, 2014. I define states PA (January 1, 2015), IN (February 1, 2015), and NH (August 15, 2014) to have expanded in 2015. I define the remaining states AK (September 1, 2015), MT (January 1, 2016), and LA (July 1, 2016) as having expanded in 2016.

Table 2.5: Triple Difference-in-Differences Results of the Effects of ACA Expansion on Health Coverage for Children by States' Expansion Status

	(1) Public	(2) ESI	(3) Non-Group	(4) Uninsured
Medicaid Eligibility (Previous) * Expand				
Previously Eligible 2014 * Yr 2014 * Expand	0.012**	-0.006	0.002	-0.009***
	(0.005)	(0.005)	(0.003)	(0.003)
Previously Eligible 2015 * Yr 2015 * Expand	0.018***	-0.015***	0.003	-0.003
	(0.005)	(0.005)	(0.003)	(0.003)
Previously Eligible 2016 * Yr 2016 * Expand	0.017***	-0.025***	0.005	0.004
	(0.005)	(0.005)	(0.003)	(0.003)
Previously Eligible 2017 * Yr 2017 * Expand	0.010*	-0.013**	0.000	0.002
	(0.005)	(0.005)	(0.003)	(0.003)
Medicaid Eligibility (New) * Expand				
Newly Eligible 2014 * Yr 2014 * Expand	0.015	0.002	0.002	-0.022***
	(0.010)	(0.010)	(0.005)	(0.006)
Newly Eligible 2015 * Yr 2015 * Expand	0.023**	0.012	-0.012**	-0.017***
	(0.010)	(0.010)	(0.005)	(0.006)
Newly Eligible 2016 * Yr 2016 * Expand	0.034***	-0.008	-0.010**	-0.011**
	(0.010)	(0.010)	(0.005)	(0.006)
Newly Eligible 2017 * Yr 2017 * Expand	0.028***	-0.005	-0.011**	-0.015***
	(0.010)	(0.010)	(0.005)	(0.006)
Medicaid Eligibility (Previous)				
Previously Eligible 2014 * Yr 2014	0.007*	-0.001	0.002	-0.006**
	(0.003)	(0.004)	(0.002)	(0.002)
Previously Eligible 2015 * Yr 2015	0.014***	0.002	0.000	-0.014***
	(0.004)	(0.004)	(0.002)	(0.002)
Previously Eligible 2016 * Yr 2016	0.020***	0.006	-0.001	-0.024***
	(0.004)	(0.004)	(0.002)	(0.002)
Previously Eligible 2017 * Yr 2017	0.028***	-0.007*	0.006**	-0.021***
	(0.004)	(0.004)	(0.002)	(0.003)
Medicaid Eligibility (New)				
Newly Eligible 2014 * Yr 2014	0.009	-0.003	-0.002	-0.003
	(0.008)	(0.008)	(0.004)	(0.005)
Newly Eligible 2015 * Yr 2015	0.036***	-0.023***	0.007*	-0.026***
	(0.008)	(0.008)	(0.004)	(0.005)
Newly Eligible 2016 * Yr 2016	0.055***	-0.023***	0.001	-0.031***
	(0.008)	(0.008)	(0.004)	(0.005)
Newly Eligible 2017 * Yr 2017	0.053***	-0.024***	0.008*	-0.029***
	(0.008)	(0.008)	(0.004)	(0.005)
Observations	3,248,152	3,248,152	3,248,152	3,248,152

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors in parentheses and clustered at the PUMA level.The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

has been demonstrated that parental eligibility and child health care utilization are positively correlated. One study found that when parents became ineligible for Medicaid, there was a significant decline in inpatient use and ER visits for their children despite them still qualifying for Medicaid (Halliday and Akee 2020).

Therefore, I follow Frean et al. (2017) and Kaestner et al. (2017) by sorting these states into a mutually exclusive category called $EarlyExpansionEligible_{ia}$. I modify equation (2.3) and redefine my model below

$$\begin{aligned} Y_{iat} = \beta_0 + \beta_1 PreviouslyEligible_{ia} + \beta_2 EarlyExpansionEligible_{ia} \\ +\beta_3 NewlyEligible2014_{ia} + \beta_4 NewlyEligible2015_{ia} \\ +\beta_5 NewlyEligible2016_{ia} + \beta_6 NewlyEligible2017_{ia} \\ +\beta_7 PreviouslyEligible_{ia} * \theta_{2014} + \beta_8 PreviouslyEligible_{ia} * \theta_{2015} \\ +\beta_9 PreviouslyEligible_{ia} * \theta_{2016} + \beta_{10} PreviouslyEligible_{ia} * \theta_{2017} \\ +\beta_{11} EarlyExpansionEligible_{ia} * \theta_{2014} + \beta_{12} EarlyExpansionEligible_{ia} * \theta_{2015} \\ +\beta_{13} EarlyExpansionEligible_{ia} * \theta_{2016} + \beta_{14} EarlyExpansionEligible_{ia} * \theta_{2017} \\ +\beta_{15} NewlyEligible2014_{ia} * \theta_{2014} + \beta_{16} NewlyEligible2015_{ia} * \theta_{2015} \\ +\beta_{17} NewlyEligible2016_{ia} * \theta_{2016} + \beta_{18} NewlyEligible2017_{ia} * \theta_{2017} \\ +\beta_x X_{iat} + \theta_t + \gamma_a + unemployment_{it} + \epsilon_{iat} \end{aligned} \tag{2}$$

where $EarlyExpansionEligible_{ia}$ equals 1 if child i, who resides in an early expansion state, is eligible for Medicaid and CHIP based on the 2013 age-year MAGI-converted thresholds in PUMA a and 0 otherwise.

Compared to Table 2.3, the coefficients for public coverage in the previously eligible population are slightly smaller in magnitude, but remain positive and significant. However, the coefficients for all health insurance variables in the newly eligible population are virtually unaffected. Among children in states that expanded Medicaid early, gains in public coverage amounted to 2.4 percentage points in 2014, 5.1 percentage points in 2015, 5.5 percentage points in 2016, and 5.3 percentage points in 2017. There is some degree of private insurance crowd-out, but the sizes of the coefficients are relatively small and are either insignificant or on the edge of significance. Overall, my estimates are relatively robust under this specification.

2.6.2 Eligibility for Premium Subsidies

Under the ACA, those with incomes between 100-400% of the FPL and residing in non-expansion states were eligible for subsidies to purchase non-group private insurance in ACA Marketplace. However, these subsidies were unavailable to individuals that received an offer to acquire ESI from their employer. Unfortunately, the ACS does not gather data on whether an individual declined their employer's offer of ESI. Therefore, I follow Hudson and Moriya (2017) and define a child as being "subsidy eligible" if they did not have ESI, resided in a non-expansion state, and had an income of between 100-400% FPL. I modify the equation (1) by including an additional parameter that indicates whether a child's parents were eligible for subsidies for non-group private insurance.

$$\begin{aligned}
Y_{iat} = \beta_0 + \beta_1 PreviouslyEligible_{ia} + \beta_2 SubsidyEligible_{ia} \\
+\beta_3 NewlyEligible2014_{ia} + \beta_4 NewlyEligible2015_{ia} \\
+\beta_5 NewlyEligible2016_{ia} + \beta_6 NewlyEligible2017_{ia} \\
+\beta_7 PreviouslyEligible_{ia} * \theta_{2014} + \beta_8 PreviouslyEligible_{ia} * \theta_{2015} \\
+\beta_9 PreviouslyEligible_{ia} * \theta_{2016} + \beta_{10} PreviouslyEligible_{ia} * \theta_{2017} \\
+\beta_{11} NewlyEligible2014_{ia} * \theta_{2014} + \beta_{12} NewlyEligible2015_{ia} * \theta_{2015} \\
+\beta_{13} NewlyEligible2016_{ia} * \theta_{2016} + \beta_{14} NewlyEligible2017_{ia} * \theta_{2017} \\
+\beta_{15} SubsidyEligible_{ia} * \theta_{2014} + \beta_{16} SubsidyEligible_{ia} * \theta_{2015} \\
+\beta_{17} SubsidyEligible_{ia} * \theta_{2016} + \beta_{18} SubsidyEligible_{ia} * \theta_{2017} \\
+\beta_x X_{iat} + \theta_t + \gamma_a + unemployment_{it} + \epsilon_{iat}
\end{aligned} \tag{3}$$

The term $SubsidyEligible_{ia}$ equals 1 if a child was eligible for the subsidy based on the criteria summarized above and 0 otherwise.[19] This will enable me to determine whether receiving premium subsidies has any effect on my results.

The coefficients for those previously eligible and newly eligible are relatively unchanged from what was reported in the main result, showing my estimates are robust to this specification. Among children who were eligible for subsidies for non-group private insurance, there is a great degree of crowd-out from public insurance to private insurance. The coefficients for ESI are all positive and significant from 2014 to 2017. However, this could be a result of the effects of the employer mandate that was more effective in non-expansion states.

[19] Note that this term is not mutually exclusive from the other eligibility terms due to children still having MAGI thresholds that deemed them eligible for Medicaid and CHIP coverage in non-expansion states.

This may also be a product of measurement error of private insurance as the wording of the ACS may influence respondents to misreport Medicaid or employer sponsored insurance as non-group private insurance (Pascale et al., 2016). This is supported by the fact that the ACS typically reports overestimates of non-group private coverage compared to other data sources (Mach and O'Hara, 2011). Lastly, the coefficients for non-group private coverage are significant starting in 2014 and highest in 2015, but start decreasing where they become negative and insignificant in 2017. A possible explanation for this could be the result of the temporary risk corridor program implemented under the ACA for 2014–2016. The program was to assist insurers in covering the unpredictable costs of enrollees with various health conditions. Ultimately, the Human Health Services (HHS) was unable to pay out the claims of the insurers. This resulted in an unexpected negative shock to revenues and the large exit of insurers such as Aetna and United from the Marketplaces in 2016 and 2017 (Layton et al., 2018).

2.7 Policy Implications and Conclusion

Since the implementation of the ACA Medicaid expansion, there have been significant gains in Medicaid and CHIP coverage for not only newly eligible recipients, but for those who were already eligible for Medicaid and CHIP prior to the expansion. Children, who had already had generally generous rates prior to and after the expansion, are an important but frequently overlooked group. Using children's MAGI threshold rates, I find significant "welcome mat" effects in public coverage for already eligible children. These effects persisted and increased across years until 2017. In addition, I find significant increases in public coverage for children who became eligible for Medicaid and CHIP. Evaluating by race and ethnicity, White children from both eligibility groups were disproportionately more likely to have benefited from the expansion. This indicates that the ACA had heterogeneous impacts on health coverage for different racial/ethnic groups. Comparing by state expansion status, both increases in Medicaid/CHIP coverage for the previously and newly eligible population was stronger in expansion states, highlighting the effectiveness of various procedures under the ACA that were adopted in these states. My results were robust to a number of specifications, including modeling for early expansion states and eligibility for private insurance subsidies. Overall, my findings show that the ACA Medicaid expansion was effective in providing public assistance to a population that otherwise should have seen minimal effects.

I also find evidence of crowding out in ESI for both previously eligible and newly eligible children from 2015 and onward. This effect was strongest for White children and in states that expanded Medicaid. To the best of my knowledge, this is the first study to prove statistically significant crowding out of private insurance for children in the setting of the ACA Medicaid expansion. This study also adds to the few studies that have established evidence of crowd-out from the ACA. This study is unique as it models for both Medicaid and CHIP eligibility rates solely children and it is inclusive of those with higher incomes. Given that previous research found only minimal effects of the ACA expansion on labor supply (Duggan et al., 2019; Garrett et al., 2017; Gooptu et al., 2016; Kaestner et al., 2017; Leung and Mas, 2018; Moriya et al., 2016), decreases in ESI coverage observed during the ACA expansion are unlikely to be attributed to changes in labor supply. Instead, my findings could reflect parental preferences for fully subsidized public coverage in lieu of costly private coverage. However, this paper is limited in that it did not seek to substantiate this claim.

The results of this paper have very important policy implications moving forward. There have been several challenges in maintaining funds for CHIP during recent years. On May 8, 2018, the Trump Administration submitted to Congress a proposal requesting a reduction of over $7 billion for the annual Children's Health Insurance Program. The proposal would have rescinded over $5.1 billion in the amounts made available by the Medicaid CHIP Reauthorization Act of 2015 to accompany the 2017 national allotments to states. This comprised $2 billion in recoveries as of May 7, 2018, and $3.1 billion in unobligated balances that were available as of October 1, 2017. The proposal would also rescind nearly $1.9 billion in amounts available for the CHIP Contingency Fund. The Contingency Fund provides payments to states that experience issues with over enrollment. Currently, Congress has extended annual funding for CHIP until September 30, 2027. However, the future of CHIP funding is unknown given the uncertainty of the political landscape moving forward. Important provisions like the MOE requirement and temporary increases in federal CHIP matching rates that are essential for delivering and maintaining continuous coverage could be eliminated if sufficient appropriations for CHIP is not secured.

This is the first paper to estimate the "welcome mat" effects of the ACA Medicaid expansions solely for children through the use of children's MAGI threshold rates. The establishment of a "welcome mat" effect highlights the importance of provisions that are currently protected in the ACA and mainly intended for children, such as the maintenance of effort (MOE) provision and enhanced federal matching funds for CHIP. However, as the appropriations for CHIP funding ends in 2027, many of these components that have protected children's eligibility for Medicaid and CHIP could cease, forcing millions of parents to find alternative sources of health coverage for their children. Therefore, this paper contributes to a narrow literature on evaluating the "welcome mat" effect for children and has important implications for policymakers, who have the potential to shape the future of CHIP.

Conclusion

This dissertation evaluated the impacts of the ACA Medicaid expansion on health coverage for both low-income childless adults and children. Specifically, I analyze how effective the expansion was in covering groups that were either intended or unintended under the policy change. In my first chapter, I found that among low-income childless adults, the probability of being a complier was highest for part-time workers compared to all other work groups. These results suggest that the characteristics that define Medicaid recipients under the ACA do not align with those that characterize them as “undeserving poor”. Moreover, my findings suggest that expanding Medicaid to non-expansion states would help reduce the ”coverage gap” that disproportionately affects Black individuals. In my second chapter, I utilized children’s eligibility limits to analyze the impacts of the ACA Medicaid expansion on Medicaid and CHIP coverage for children. Children were primarily eligible for Medicaid and CHIP prior to the expansion and therefore were not an intended target group for the ACA expansion. My results showed a modest uptake in Medicaid and CHIP coverage for children who were previously eligible for these programs prior to expansion. However, I also found some degree of crowding out in private insurance for this same population. This not only validates the effectiveness of the ACA Medicaid on children’s outcomes, but may also highlight parents’ preferences for fully subsidized public coverage over costly private coverage for their children.

Overall, the evidence supports the sustained implementation of Medicaid expansion as a means of boosting access to healthcare and improving health outcomes for both adults and children. However, issues persist in ensuring that Medicaid programs are fiscally sustainable and available to all medically needy populations. Medicaid and CHIP’s fiscal futures are uncertain as lawmakers seek to cut both programs in order to balance budgets and reduce the federal deficit. Critics, however, claim that these cuts will disproportionately harm low-income households and children, who rely significantly on these programs for access to health care services. Conducting further research to investigate the effectiveness of Medicaid expansion programs in improving healthcare access, patient health outcomes, and reducing costs for the populations they serve is crucial. By providing stronger evidence, such research can inform efforts to design and implement Medicaid expansion programs that achieve the best possible outcomes for individuals and communities.

Appendix A

Chapter One Appendix

A.1 Tables

Table A.1: Event Study Results of Expansion on Medicaid Coverage: Childless Adults (0-138% FPL)

	(1) Medicaid	(2) Private	(3) Uninsured
Year -4	0.003	-0.005	0.001
	(0.006)	(0.005)	(0.008)
Year -3	-0.003	0.003	-0.005
	(0.006)	(0.005)	(0.006)
Year -2	-0.002	-0.007	0.006
	(0.004)	(0.005)	(0.006)
Year 0	0.116***	-0.055***	-0.058***
	(0.012)	(0.006)	(0.015)
Year 1	0.196***	-0.079***	-0.112***
	(0.019)	(0.007)	(0.021)
Year 2	0.205***	-0.086***	-0.127***
	(0.019)	(0.008)	(0.021)
Year 3	0.204***	-0.078***	-0.117***
	(0.020)	(0.007)	(0.020)
Observations	621509	621509	621509
Year FEs	✓	✓	✓
State FEs	✓	✓	✓

Notes: The sample is restricted to non-disabled childless adults aged 26-64 with incomes below 138% of the FPL. Standard errors are clustered at the state-year level and are provided in parentheses (*** p<0.01, ** p<0.05, * p<0.10). Each cell reports the results from regressing the main effects of policy variables outlined in equation (1.6) and several controls on different types of health insurance indicators across two different income samples. Controls include gender, race/ethnicity, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates are weighted using ACS weights.

Table A.2: Observable Characteristics for the Always Takers, Compliers and Never Takers Childless Adults (0-138% FPL)

	(1) AT	(2) C	(3) NT	(4) Mean
Work Status				
Does Not Work	71.8	43.3	42.0	47.2
Part-Time	16.8	28.3	26.0	25.0
Full-Time	11.4	28.9	32.1	27.7
Race/Ethnicity				
Non-Hispanic White	48.3	56.6	55.3	54.3
Non-Hispanic Black	29.7	24.7	14.1	19.9
Hispanic	15.3	15.3	19.0	17.6
Gender				
Female	53.9	50.2	47.8	49.4
Education				
Less Than High School	30.0	23.1	16.7	20.8
High School	37.3	38.0	31.5	34.0
Some College	24.8	30.0	27.9	27.8
College/Advanced	8.0	7.3	23.8	17.3
Income Group				
0-50% FPL	17.6	19.2	18.9	18.7
50-100% FPL	44.9	34.3	30.6	33.9
100-138% FPL	25.4	34.0	32.3	31.5

Table A.3: Conditional Probability of Being a Complier in Non-Expansion States (0-138% FPL)

	(1) $P(C\,|\,Black)$	(2) $P(C\,|\,White)$	(3) Δ (1-2)	(4) Population, Black (%)
States				
Alabama (AL)	16.0 (0.5)	15.3 (0.5)	0.7	38.3%
Georgia (GA)	14.1 (0.2)	13.1 (0.3)	1.0	40.1%
Florida (FL)	16.3 (0.3)	15.6 (0.4)	0.7	18.2%
Kansas (KS)	17.9 (0.4)	16.2 (0.9)	1.7	8.1%
Mississippi (MS)	16.9 (0.4)	14.9 (0.4)	2.0	55.8%
North Carolina (NC)	15.9 (0.2)	14.1 (0.4)	1.8	31.6%
South Carolina (SC)	14.9 (0.4)	13.8 (0.5)	1.1	38.2%
Tennessee (TN)	17.3 (0.3)	16.2 (0.4)	1.1	22.2%
Texas (TX)	16.1 (0.3)	14.6 (0.4)	1.5	16.7%
Wyoming (WY)	11.9 (0.2)	14.6 (5.4)	-2.7	1.4%

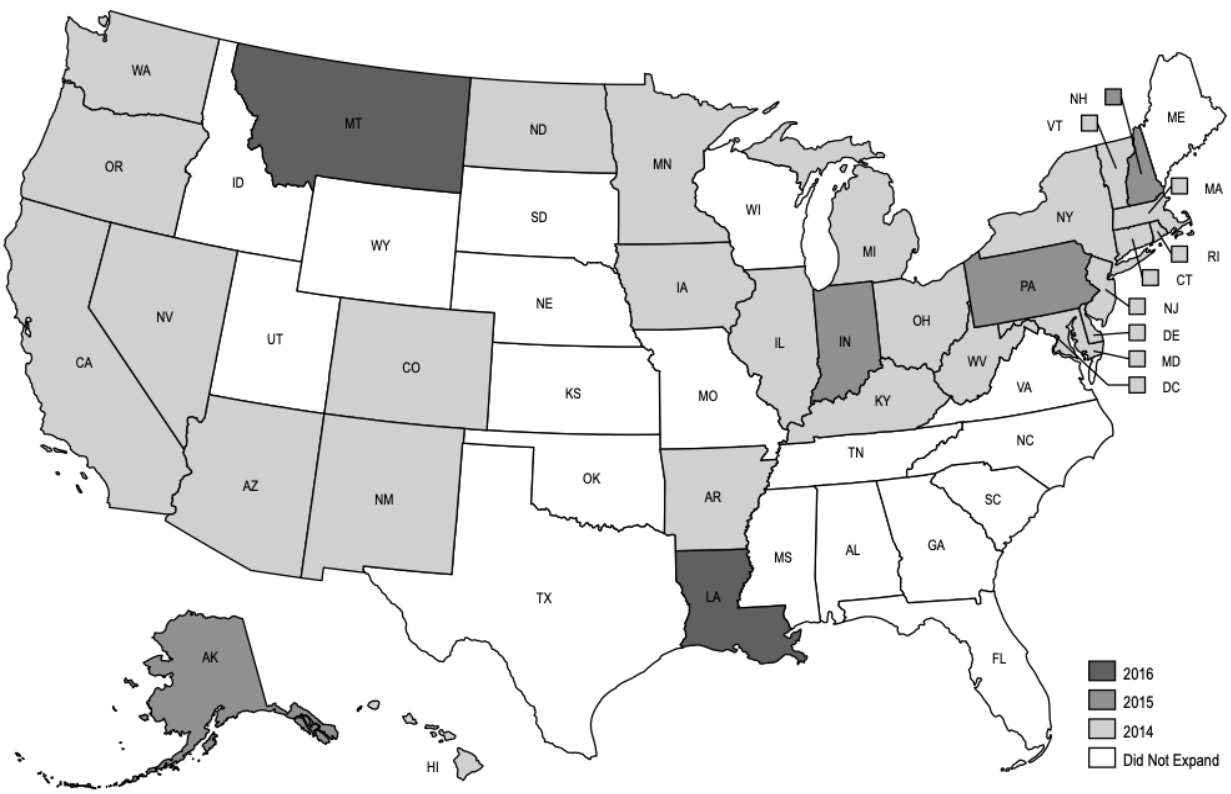
Table A.4: Conditional Probability of Being a Complier in the Top Ten States with the Highest Percentage of Black Childless Adults (0-138% FPL)

	(1) $P(C \mid Black)$	(2) $P(C \mid White)$	(3) Δ (1-2)	(4) Population, Black (%)	(5) Year Expanded
States					
Mississippi (MS)	16.9 (0.4)	14.9 (0.4)	2.0	55.8%	-
Louisiana (LA)	19.4 (0.4)	18.0 (0.5)	1.4	44.7%	2017
Georgia (GA)	14.1 (0.2)	13.1 (0.3)	1.0	40.1%	-
Alabama (AL)	16.0 (0.5)	15.3 (0.5)	0.7	38.3%	-
South Carolina (SC)	14.9 (0.4)	13.8 (0.5)	1.1	38.2%	-
Maryland (MD)	19.5 (0.3)	20.3 (0.5)	-0.8	37.5%	2014
North Carolina (NC)	15.9 (0.2)	14.1 (0.4)	1.8	31.6%	-
Virginia (VA)	14.6 (0.4)	13.6 (0.5)	1.0	27.4%	2019[a]
Delaware (DE)	20.2 (0.5)	22.3 (0.9)	-2.1	27.1%	2014
Arkansas (AR)	17.0 (0.5)	17.7 (0.7)	-0.7	23.3%	2014

[a]Note that this is not observed as the data used in this analysis is from 2010 to 2017.

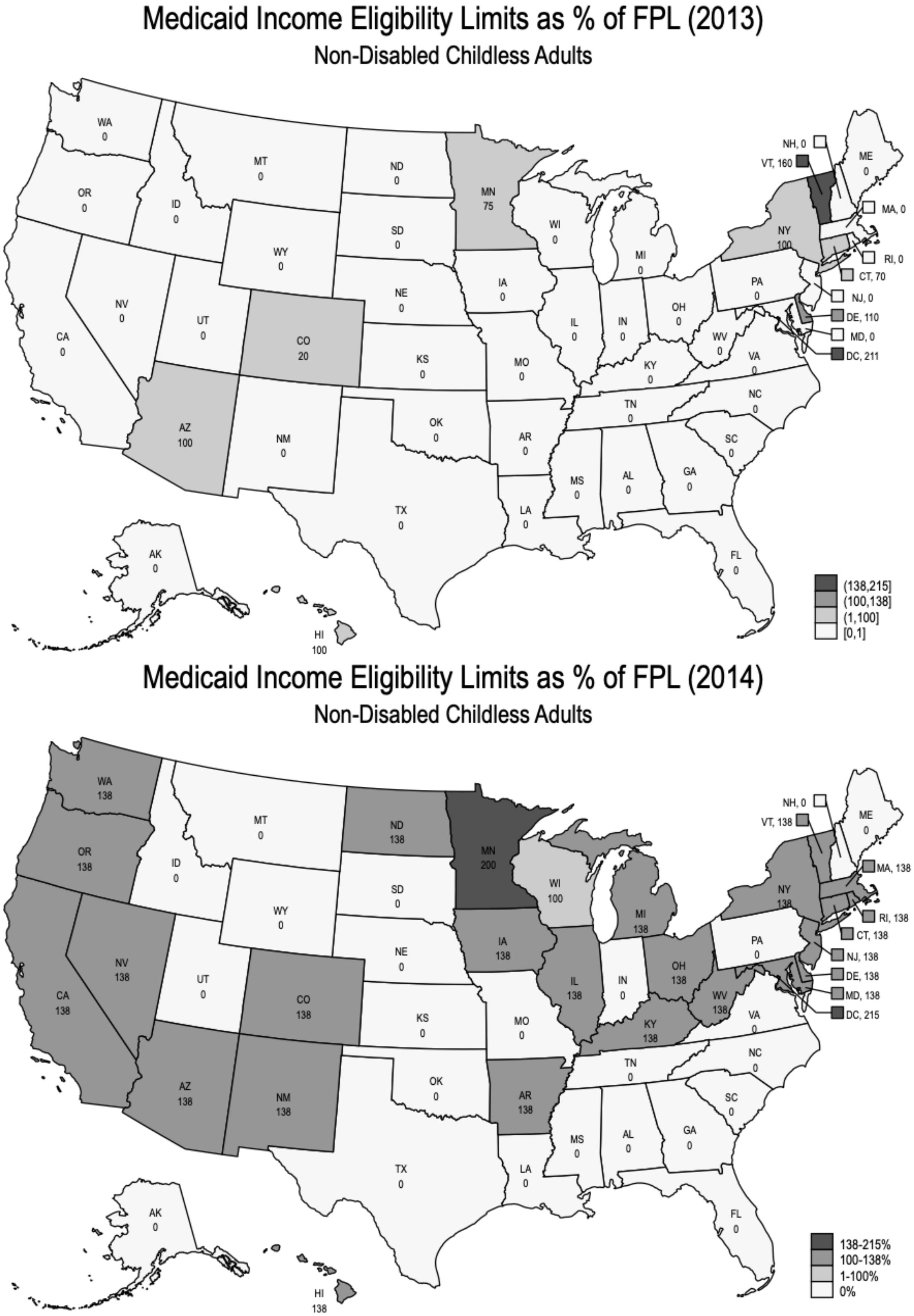
A.2 Figures

Figure A.1: ACA Medicaid Expansion Status (2014-2017)



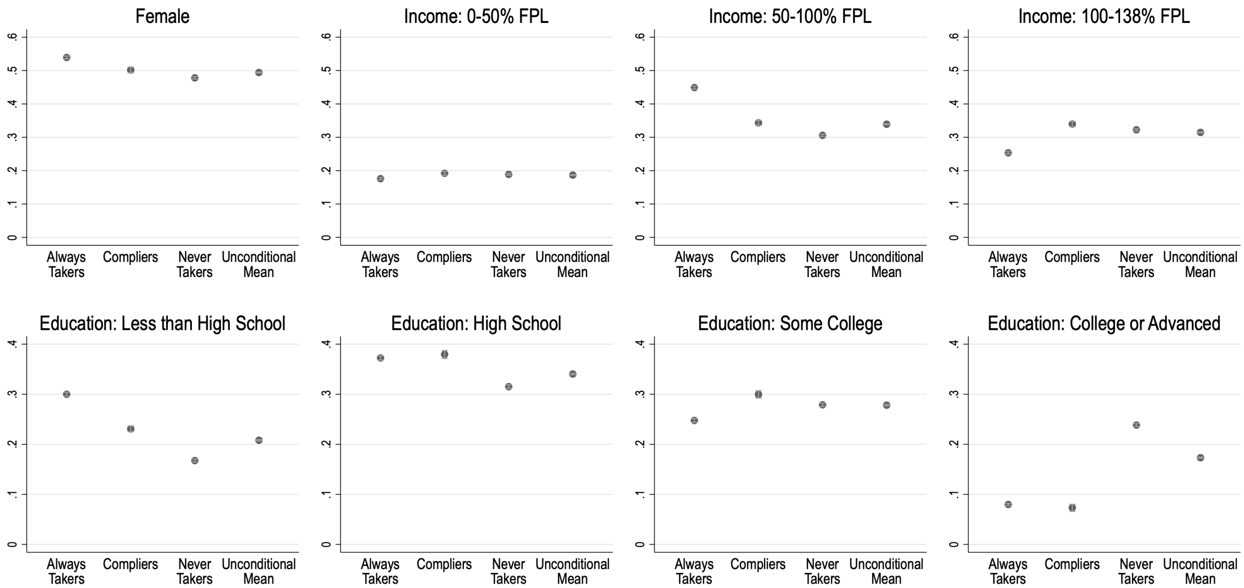
Notes: Figure was created by author using information on states' expansion status from the Kaiser Family Foundation (KFF).

Figure A.2: Medicaid Income Eligibility Limits as % of FPL (2013-2014)



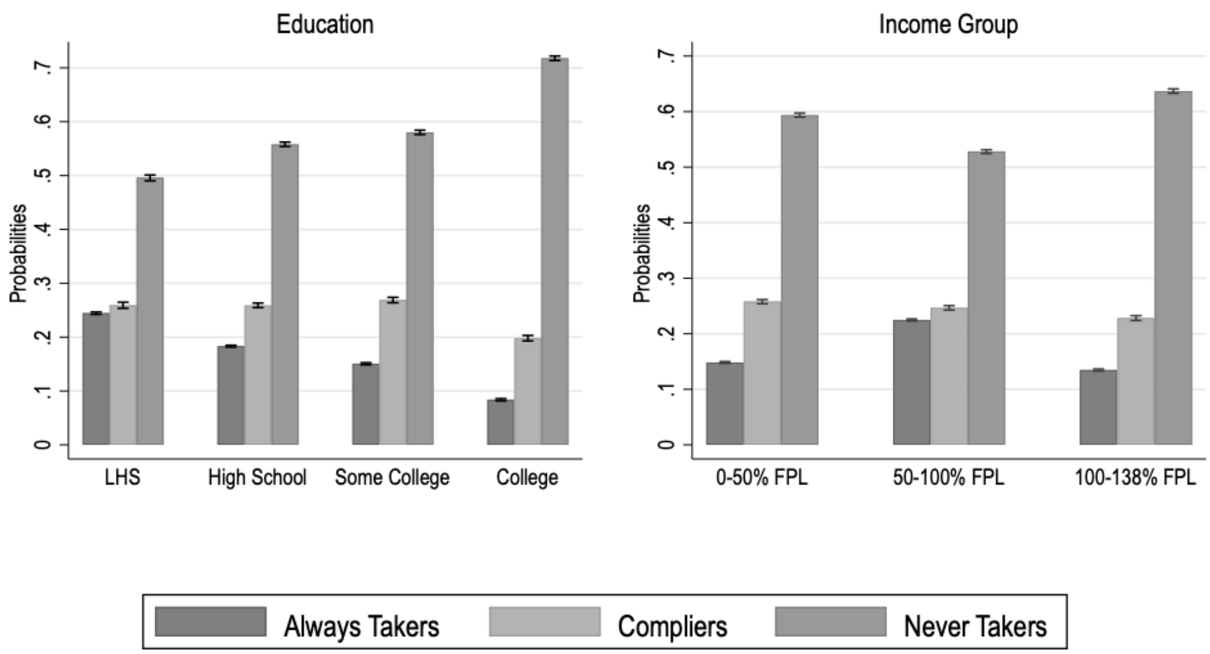
Notes: Figure was created by author using information on states' Medicaid eligibility thresholds rates from the Kaiser Family Foundation (KFF).

Figure A.3: Other Observable Characteristics for the Always Takers, Compliers, and Never Takers: Childless Adults (0-138% FPL)



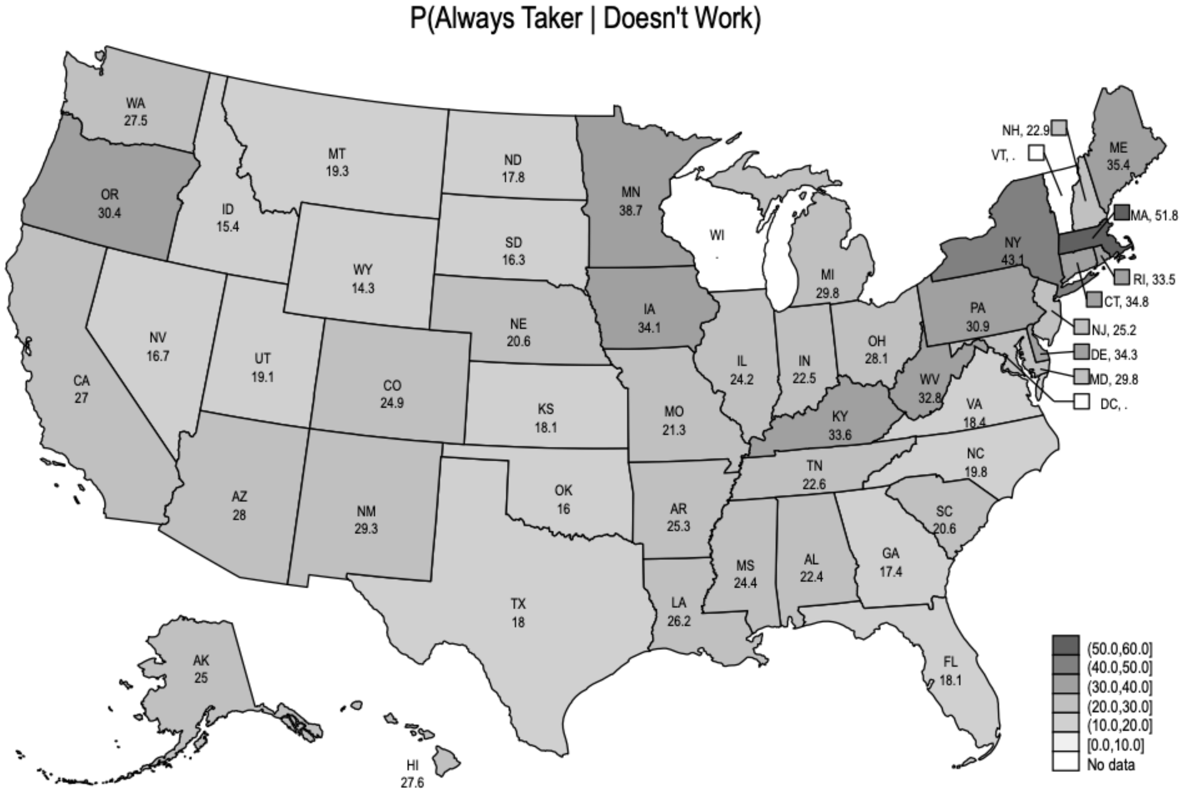
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

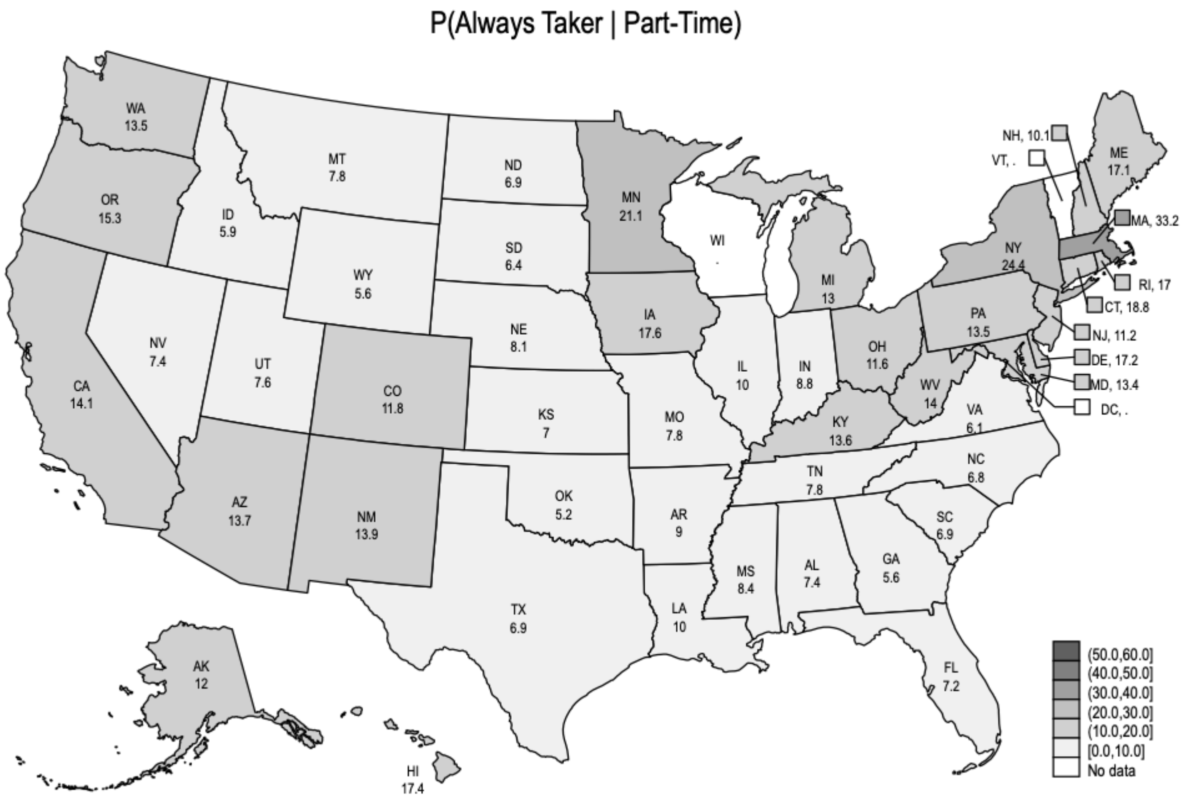
Figure A.4: Conditional Probabilities of the Always Takers, Compliers, and Never Takers: Income Group and Education, Childless Adults (0-138% FPL)



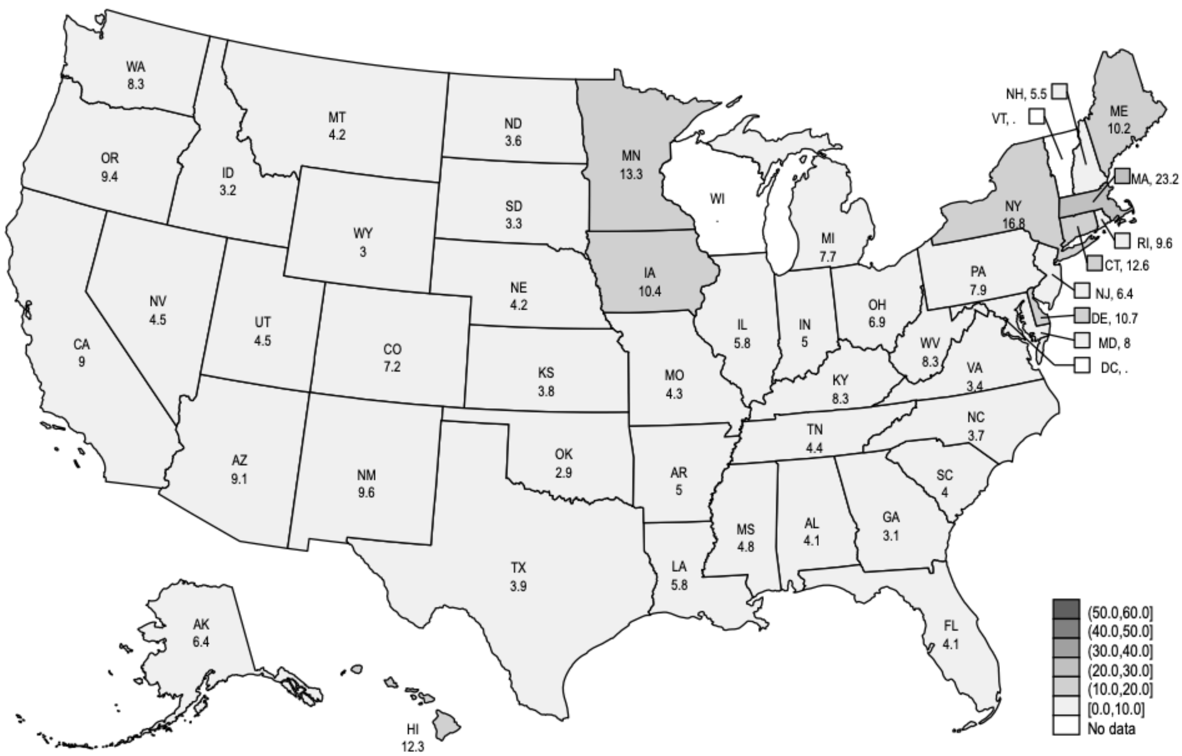
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A.5: State-Level Conditional Probabilities of the Always Takers: Work Status, Childless Adults (0-138% FPL)



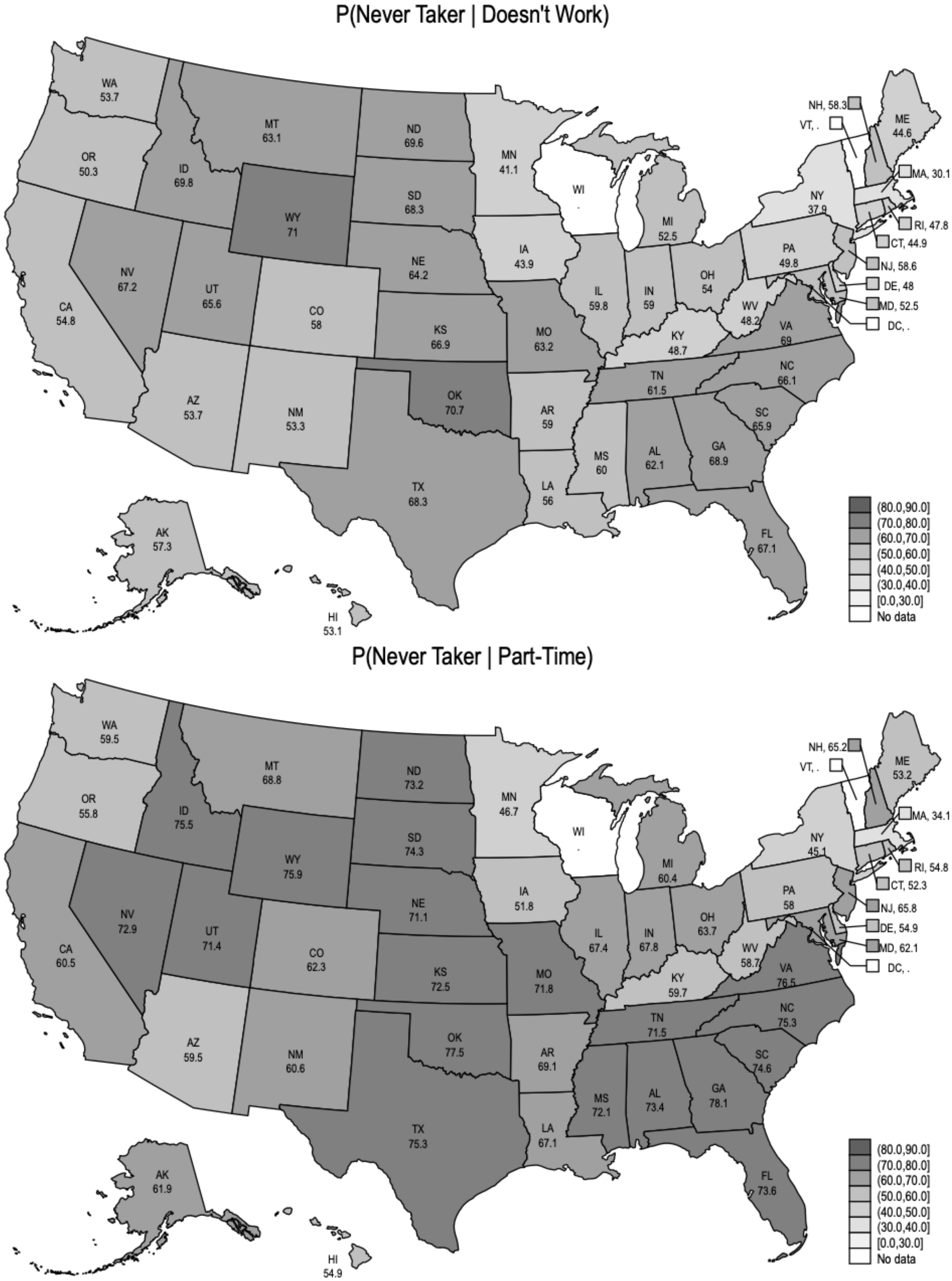


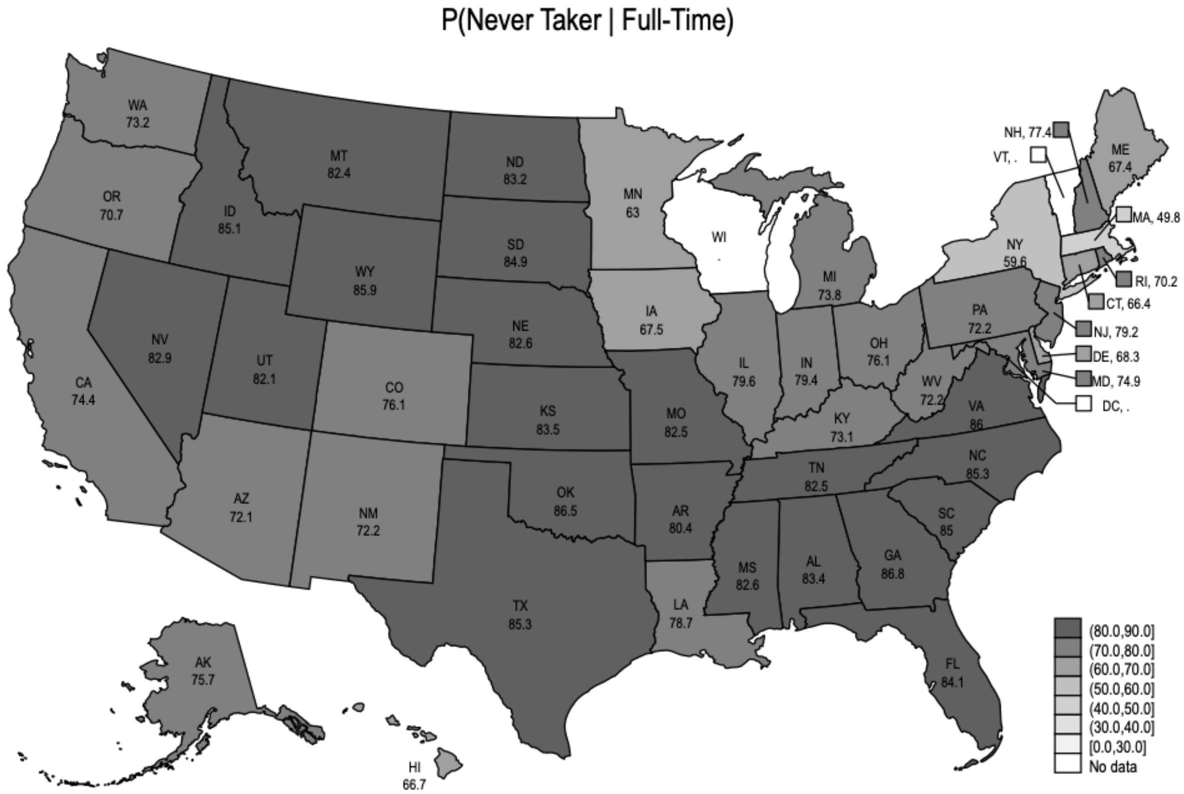
P(Always Taker | Full-Time)



Notes: I report the estimates on the probability of being an always taker for each state using a saturated probit model and methods from Abadie (2003). Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

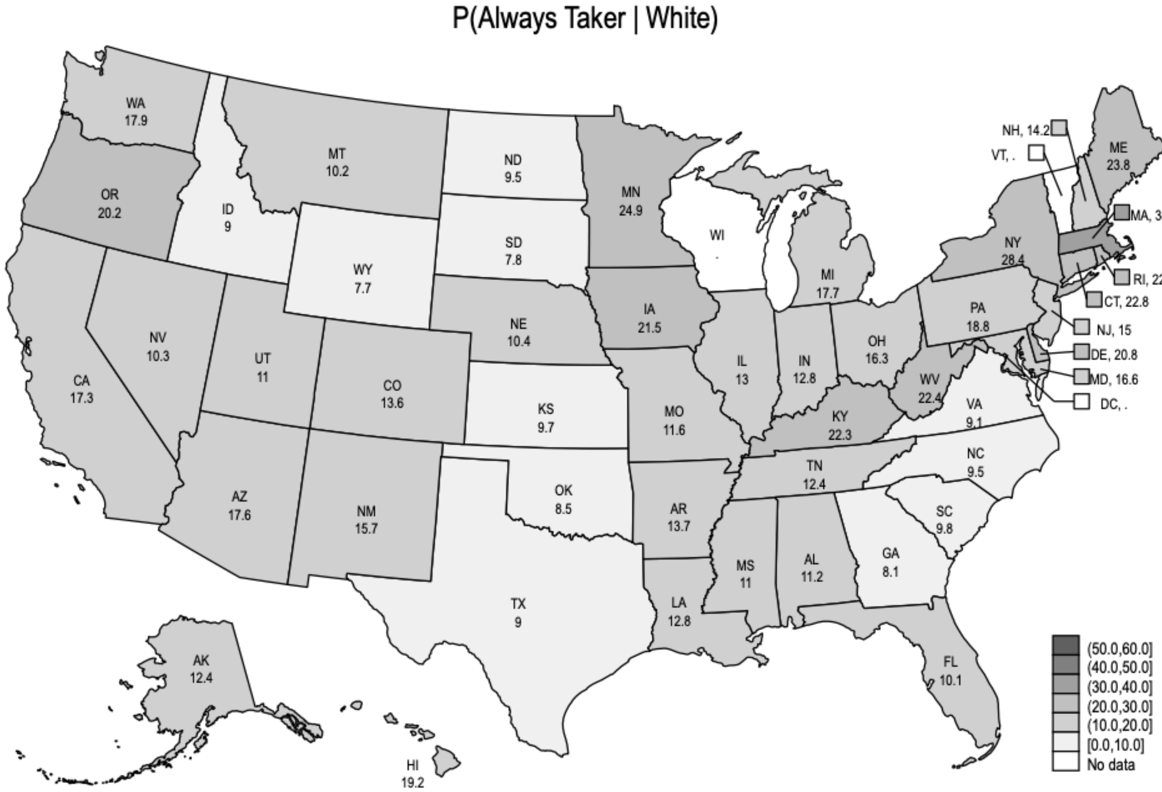
Figure A.6: State-Level Conditional Probabilities of the Never Takers: Work Status, Childless Adults (0-138% FPL)

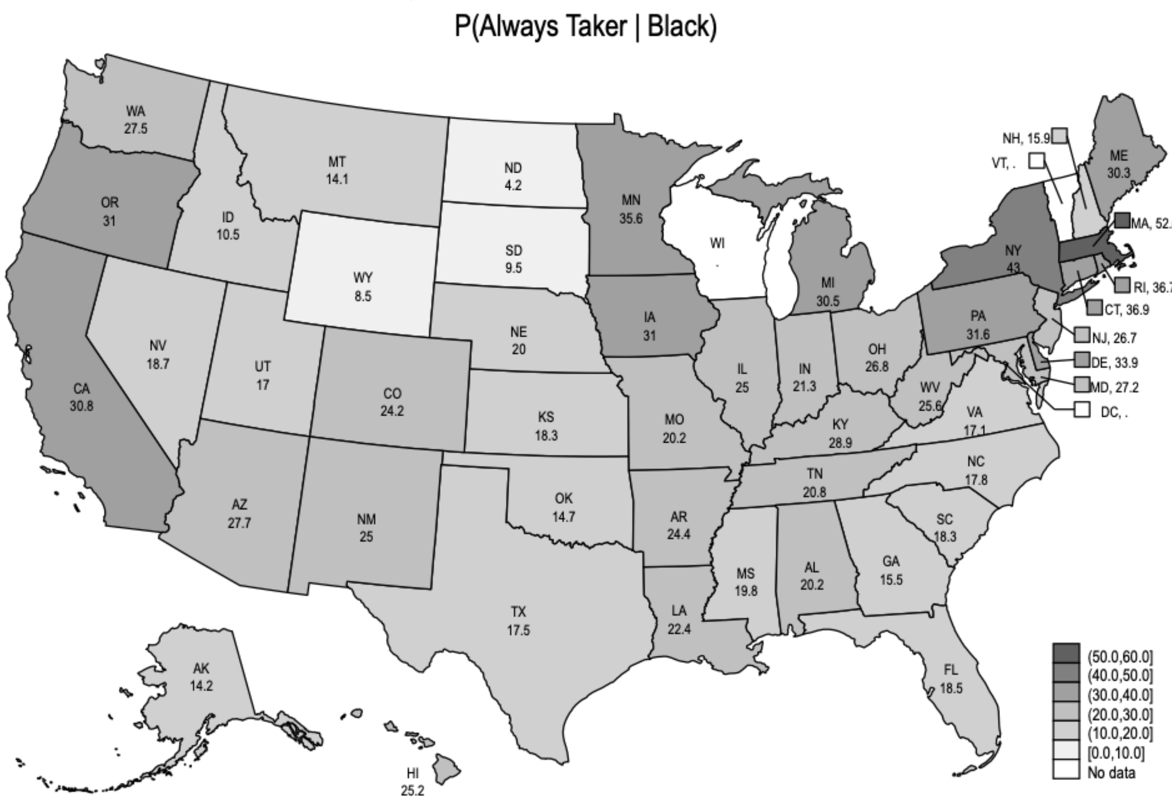


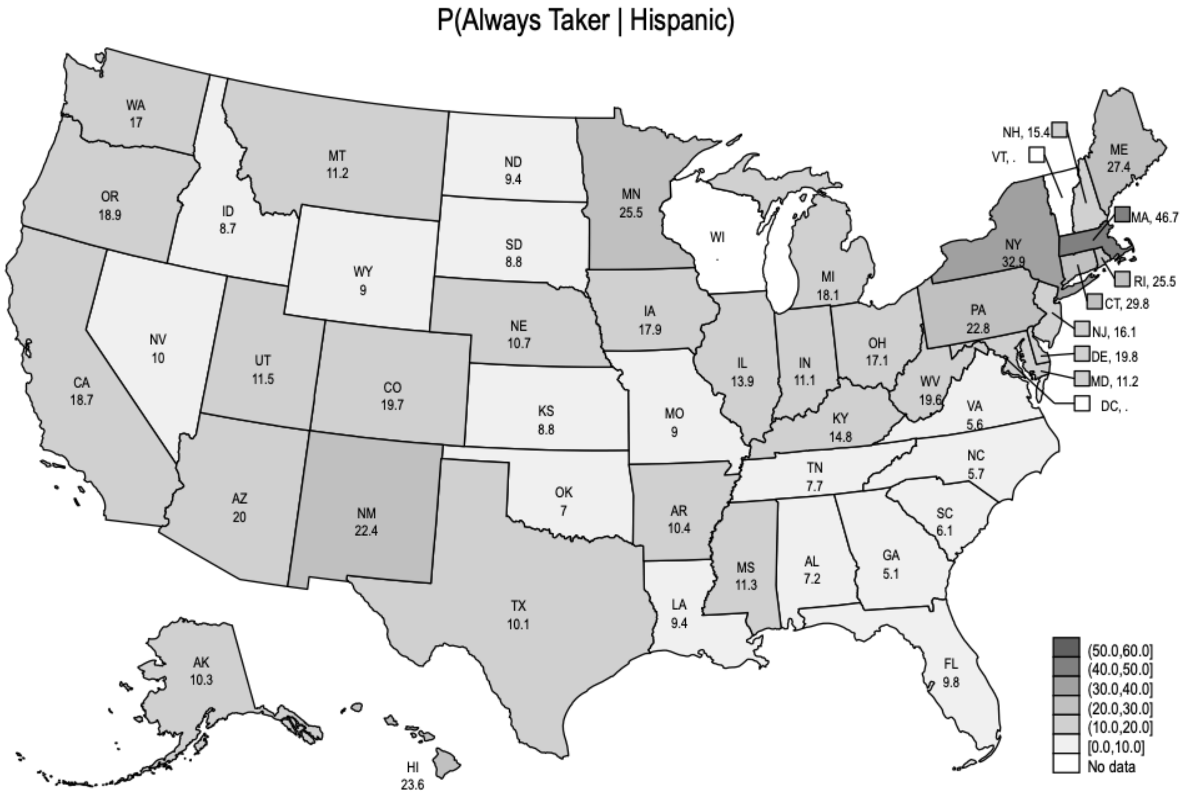


Notes: I report the estimates on the probability of being a never taker for each state using a saturated probit model and methods from Abadie (2003). These include counterfactual estimates for non-expansion states or the probability of being a never taker if that state had expanded Medicaid in 2014. Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

Figure A.7: State-Level Conditional Probabilities of the Always Takers: Race/Ethnicity, Childless Adults (0-138% FPL)

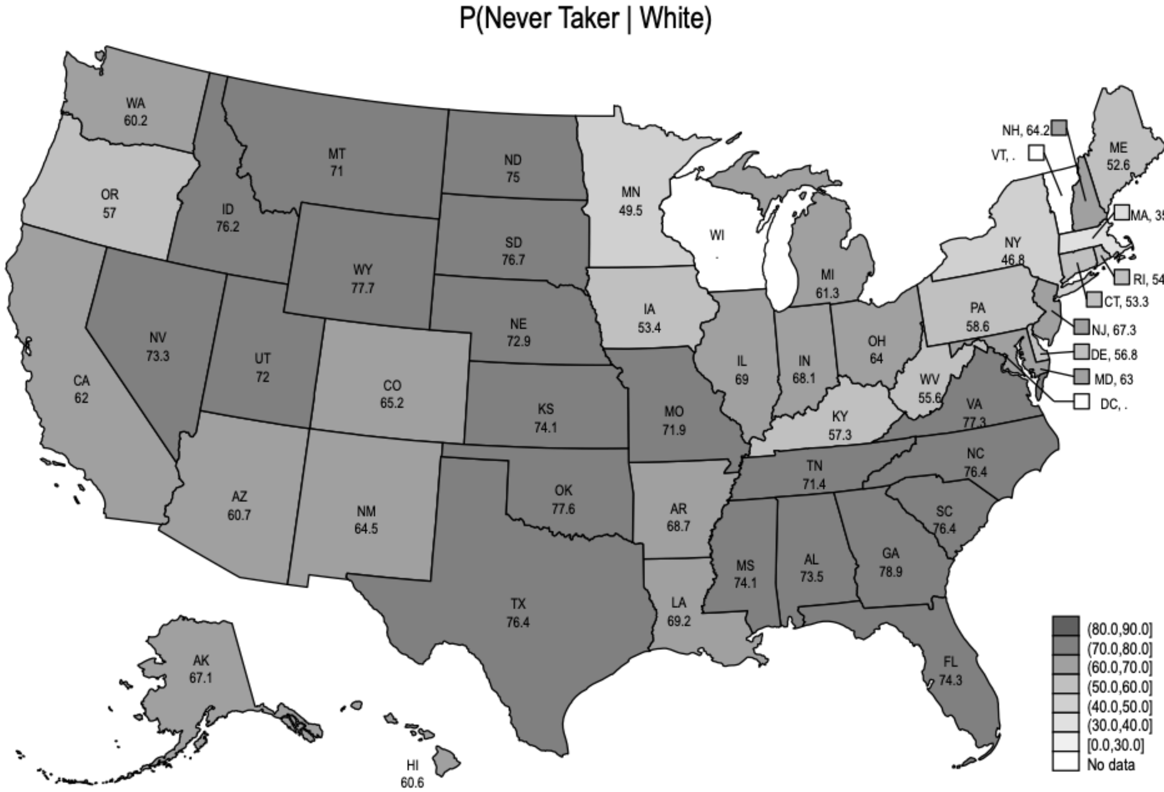


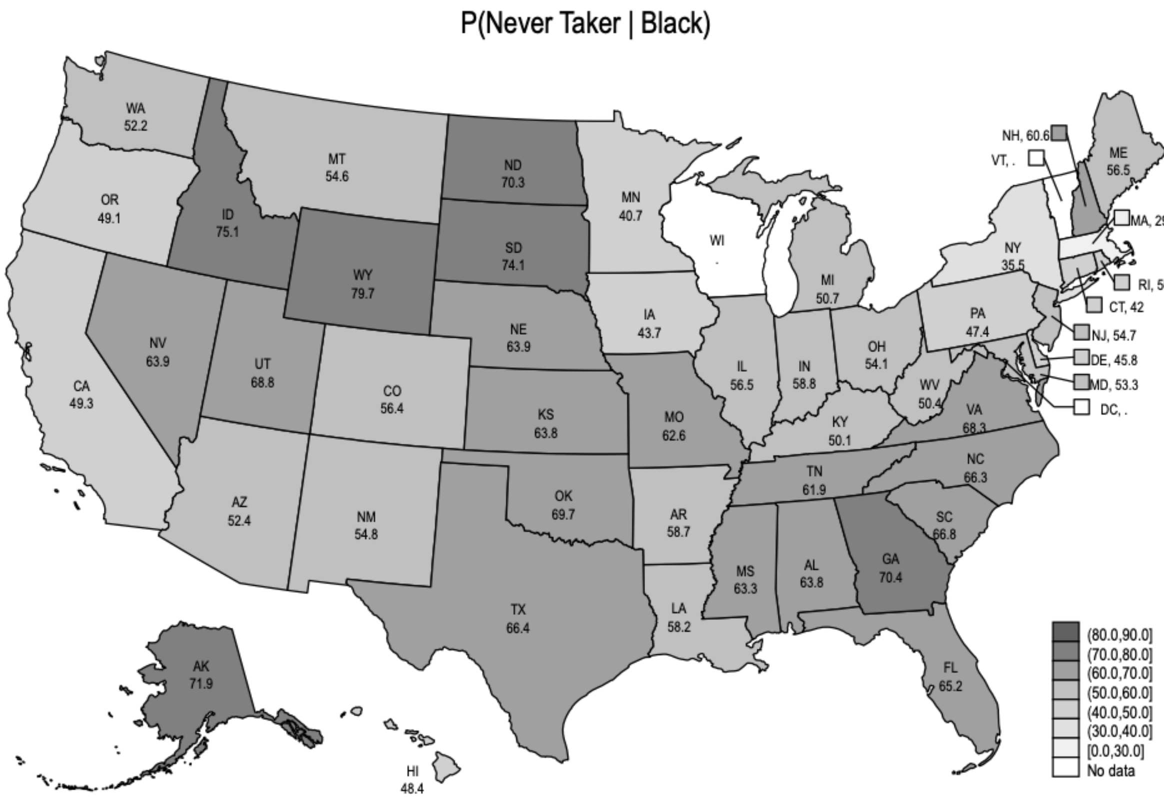


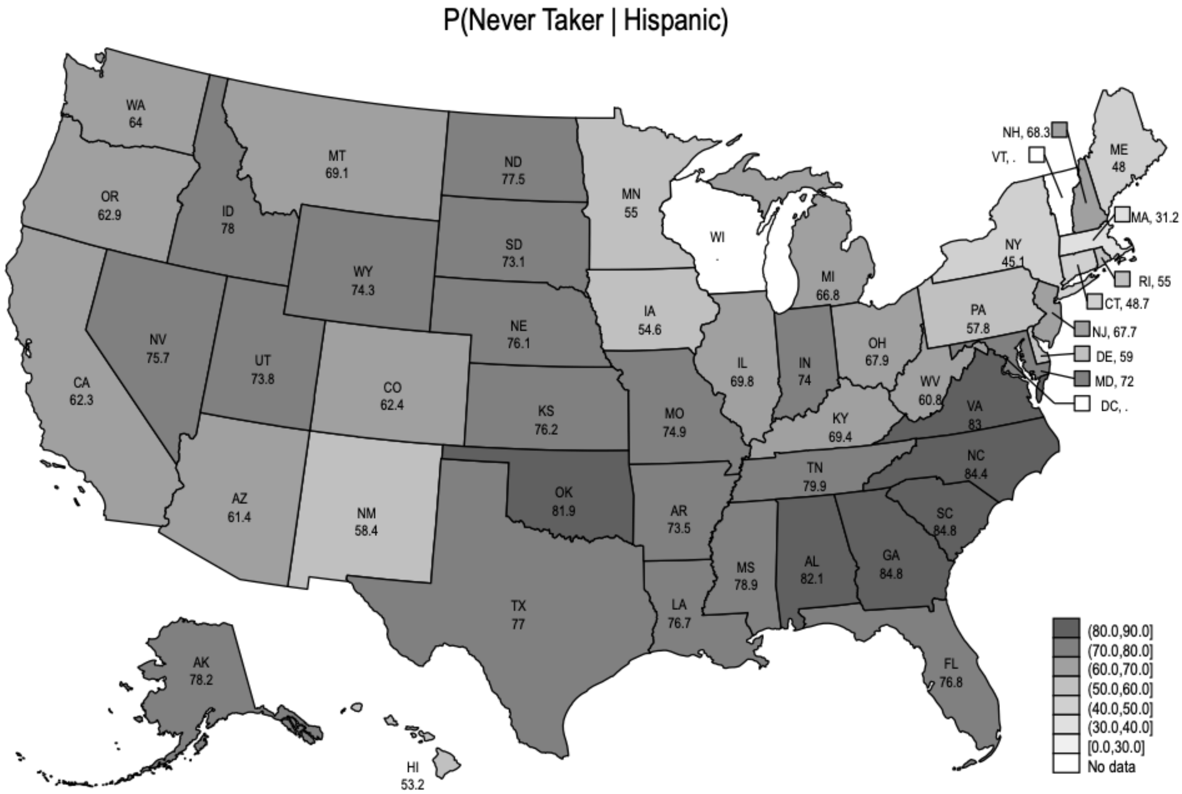


Notes: I report the estimates on the probability of being an always taker for each state using a saturated probit model and methods from Abadie (2003). Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

Figure A.8: State-Level Conditional Probabilities of the Never Takers: Race/Ethnicity, Childless Adults (0-138% FPL)







Notes: I report the estimates on the probability of being a never taker for each state using a saturated probit model and methods from Abadie (2003). These include counterfactual estimates for non-expansion states or the probability of being a never taker if that state had expanded Medicaid in 2014. Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

A.3 Staggered Treatment Design

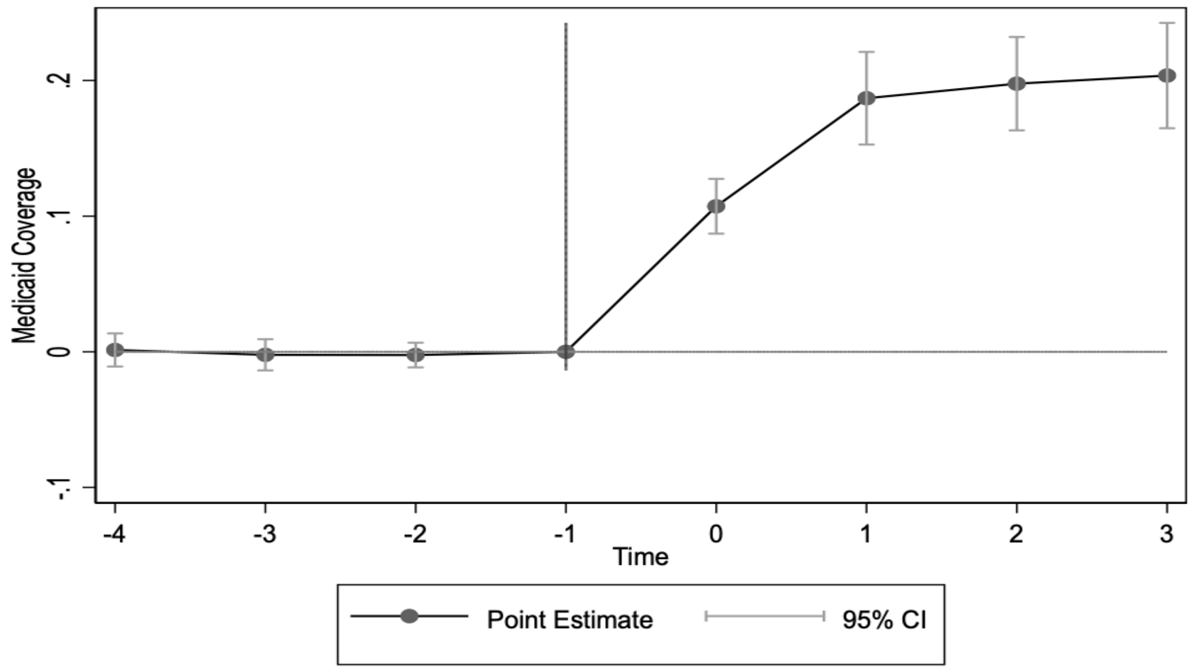
Recently, researchers have been concerned with accurately interpreting the estimates from DID models with variations in treatment timing. In particular, if there are heterogeneous treatment effects across treatment cohorts, then the strict exogeneity assumption is violated. This is caused by the composite error term being correlated with both the treatment variable and group fixed effects. Thus, the parallel trends assumption is not in itself a sufficient condition for identification in the presence of heterogeneous treatment effects.

In my design, there are three treatment cohorts, with nineteen states expanding Medicaid in 2014, three states expanding in 2015, and three states expanding in 2016. Sun and Abraham (2021) showed that the coefficients from the TWFE model on lead and lag indicators will be contaminated with information from other leads and lags. To formally test this, I employed the alternative estimation method proposed in their study. Following their methodology, I calculate the weighted average of the cohort average treatment effect on the treated (CATT) for each cohort (Sun, 2021). I report the event study results from this approach in figure A.9 in the appendix. The point estimates across time periods are statistically no different from the main result, showing that the variation in treatment timing is not a concern in my study.

In relation to a staggered treatment design, Goodman-Bacon (2021) argued that the presence of time-varying treatment effects could potentially lead to a biased DD estimate. Issues could arise when states that have already expanded are set as a control for states that expanded after the initial ACA Medicaid expansion in 2014. This is problematic since the 2x2 DD estimate is a weighted average of all two-group DD estimators. However, Miller et al. (2021) argued that this is unlikely to be a concern, with regards to the ACA Medicaid expansion, as there are few late adopter states and a relatively short time period.

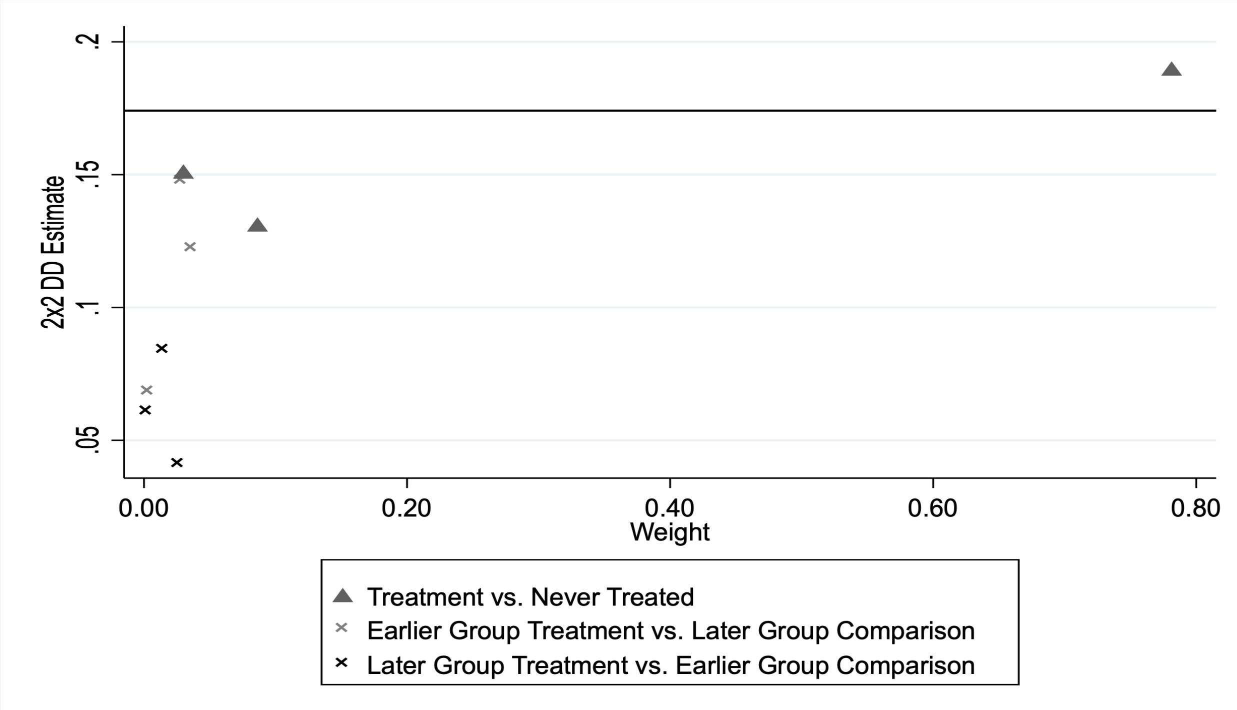
To formally test this, I implement the Goodman-Bacon decomposition that describes the weight and magnitude of the coefficients from each of the 2x2 DD comparisons on the overall two-way fixed effect DD estimate (Goodman-Bacon et al., 2019). Table A.5 in the appendix shows that only 4% of the DD estimate is derived from comparisons between the later-treated and earlier-treated (set as comparison) states. Combined with the small magnitudes of the coefficients, the overall DD estimate does not significantly differ from what is reported in the main paper.

Figure A.9: Event Study (Sun and Abraham, 2020) of the ACA Medicaid Expansion: Childless Adults (0-138% FPL)



Notes: Each panel reports the coefficients from using an alternative "interaction-weighted" estimator introduced in Sun and Abraham (2021). See section A.3 in the appendix for more details.

Figure A.10: Bacon Decomposition of the ACA Medicaid Expansion: Childless Adults (138% FPL)



Notes: Each panel reports the coefficients from using the DD decomposition outlined in Goodman-Bacon (2021). See section A.3 for more details.

Table A.5: Bacon-Decomposition of the ACA Expansion on Medicaid Coverage for Childless Adults (138% FPL)

DD Comparison	Weight	Average DD Estimate
Earlier T vs. Later C	0.064	0.132
Later T vs. Earlier C	0.039	0.057
T vs. Never treated	0.898	0.182

Treatment=T; Comparison=C

Appendix B

Chapter Two Appendix

B.1 Tables

Table B.1: Summary Statistics for Control Variables

	Mean	SD
Child's Demographics		
Female	0.49	0.50
Age	9.02	5.36
Has Disability	0.04	0.20
Race/Ethnicity: Non-Hispanic White	0.54	0.50
Race/Ethnicity: Non-Hispanic Black	0.15	0.36
Race/Ethnicity: Hispanic	0.23	0.42
Household Income (% of the FPL)	273.04	167.64
Number of Related Children in Household	2.34	1.24
Mother's Demographics		
Age	38.01	7.87
Married	0.73	0.44
Education: No High School Degree	0.12	0.32
Education: High School Degree	0.21	0.41
Education: Some College	0.33	0.47
Education: College Degree or More	0.34	0.48
Work Status: Doesn't Work	0.28	0.45
Work Status: Part-Time	0.21	0.41
Work Status: Full-Time	0.51	0.50
Father's Demographics		
Age	40.63	8.44
Married	0.90	0.30
Educational Attainment (Less than Highschool)	0.13	0.33
Educational Attainment (At Least Highschool)	0.24	0.43
Educational Attainment (Some College)	0.22	0.42
Educational Attainment (College or More)	0.49	0.50
Work Status (No Work)	0.06	0.23
Work Status (Part Time)	0.06	0.24
Work Status (Full Time)	0.91	0.29
Observations	3,386,074	

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors in parentheses and clustered at the PUMA level. The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

Table B.2: Difference-in-Differences Results of the Effects of ACA Expansion on Health Coverage for Children, Including Early Expansion States

	(1) Public	(2) ESI	(3) Non-Group	(4) Uninsured
Medicaid Eligibility (Previous)				
Previously Eligible 2014 * Yr 2014	0.010***	-0.004	0.004**	-0.009***
	(0.003)	(0.003)	(0.002)	(0.002)
Previously Eligible 2015 * Yr 2015	0.021***	-0.006**	0.004**	-0.014***
	(0.003)	(0.003)	(0.002)	(0.002)
Previously Eligible 2016 * Yr 2016	0.026***	-0.009***	0.004**	-0.020***
	(0.003)	(0.003)	(0.002)	(0.002)
Previously Eligible 2017 * Yr 2017	0.031***	-0.016***	0.009***	-0.018***
	(0.003)	(0.003)	(0.002)	(0.002)
Medicaid Eligibility (Early)				
Early Eligible 2014 * Yr 2014	0.024***	-0.005	0.001	-0.018***
	(0.005)	(0.005)	(0.003)	(0.003)
Early Eligible 2015 * Yr 2015	0.051***	-0.016***	-0.002	-0.028***
	(0.005)	(0.005)	(0.003)	(0.003)
Early Eligible 2016 * Yr 2016	0.055***	-0.014***	-0.006	-0.030***
	(0.006)	(0.005)	(0.004)	(0.003)
Early Eligible 2017 * Yr 2017	0.053***	-0.016***	-0.001	-0.029***
	(0.006)	(0.005)	(0.004)	(0.003)
Medicaid Eligibility (New)				
Newly Eligible 2014 * Yr 2014	0.018***	-0.001	-0.001	-0.017***
	(0.005)	(0.005)	(0.003)	(0.003)
Newly Eligible 2015 * Yr 2015	0.052***	-0.016***	-0.001	-0.037***
	(0.005)	(0.005)	(0.003)	(0.003)
Newly Eligible 2016 * Yr 2016	0.079***	-0.029***	-0.005**	-0.039***
	(0.005)	(0.005)	(0.002)	(0.003)
Newly Eligible 2017 * Yr 2017	0.073***	-0.029***	0.001	-0.040***
	(0.005)	(0.005)	(0.003)	(0.003)
Policy Controls				
Previously Eligible	0.024***	-0.018***	-0.005***	0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Early Eligible	0.010**	-0.019***	0.004	0.002
	(0.005)	(0.004)	(0.003)	(0.003)
Newly Eligible 2014	0.009	-0.036**	0.013	0.008
	(0.018)	(0.017)	(0.009)	(0.007)
Newly Eligible 2015	0.034*	-0.025	-0.011	0.007
	(0.019)	(0.018)	(0.009)	(0.008)
Newly Eligible 2016	-0.045	0.066*	0.037*	-0.064**
	(0.035)	(0.040)	(0.021)	(0.027)
Newly Eligible 2017	0.013	-0.028	-0.041**	0.065**
	(0.034)	(0.039)	(0.021)	(0.027)
Observations	3,248,152	3,248,152	3,248,152	3,248,152

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors in parentheses and clustered at the PUMA level.The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

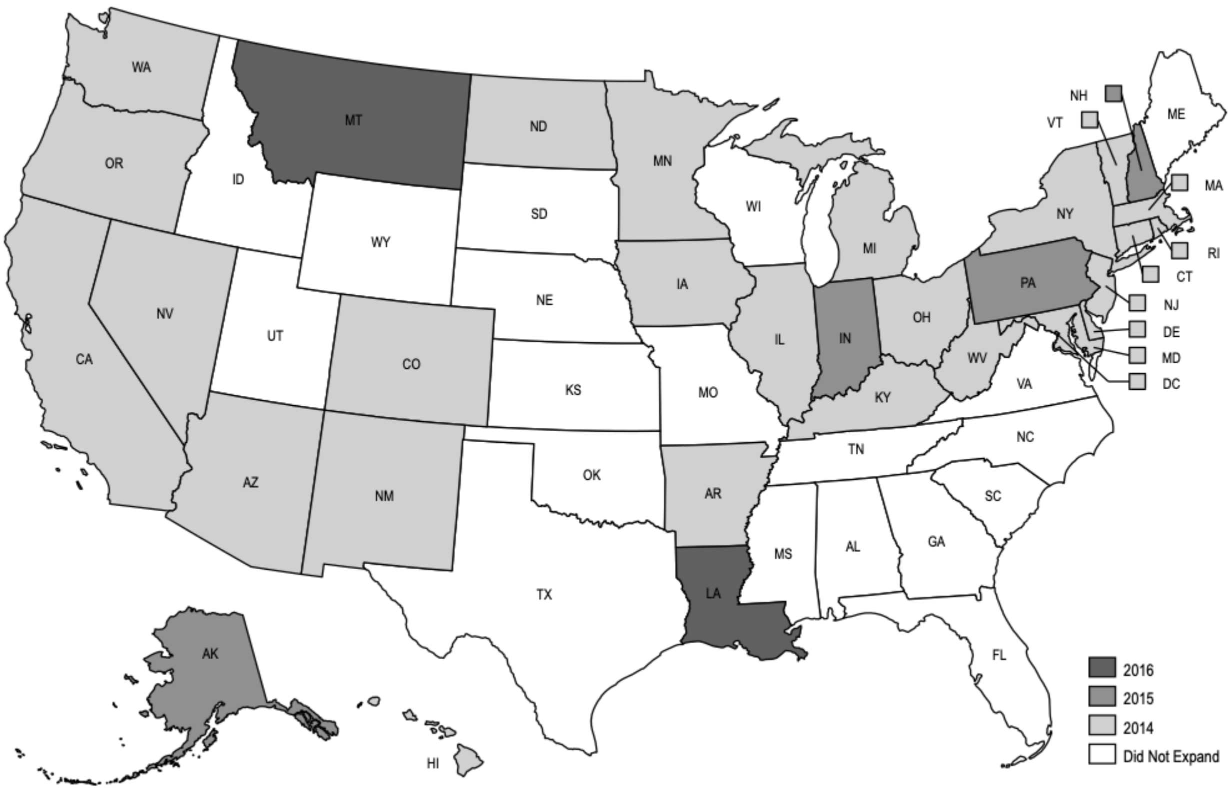
Table B.3: Difference-in-Differences Results of the Effects of ACA Expansion on Health Coverage for Children, Including Eligibility for Marketplace Subsidies

	(1) Public	(2) ESI	(3) Non-Group	(4) Uninsured
Medicaid Eligibility (Previous)				
Previously Eligible 2014 * Yr 2014	0.013***	-0.004*	0.004***	-0.011***
	(0.002)	(0.003)	(0.001)	(0.001)
Previously Eligible 2015 * Yr 2015	0.026***	-0.004*	0.002	-0.018***
	(0.002)	(0.002)	(0.002)	(0.001)
Previously Eligible 2016 * Yr 2016	0.031***	-0.006**	0.002	-0.023***
	(0.003)	(0.003)	(0.002)	(0.001)
Previously Eligible 2017 * Yr 2017	0.034***	-0.011***	0.004**	-0.021***
	(0.003)	(0.003)	(0.002)	(0.001)
Medicaid Eligibility (New)				
Newly Eligible 2014 * Yr 2014	0.018***	-0.001	-0.000	-0.017***
	(0.005)	(0.005)	(0.003)	(0.003)
Newly Eligible 2015 * Yr 2015	0.051***	-0.013***	-0.001	-0.038***
	(0.005)	(0.005)	(0.003)	(0.003)
Newly Eligible 2016 * Yr 2016	0.078***	-0.026***	-0.006**	-0.040***
	(0.005)	(0.005)	(0.002)	(0.003)
Newly Eligible 2017 * Yr 2017	0.072***	-0.024***	-0.002	-0.041***
	(0.005)	(0.005)	(0.003)	(0.003)
Subsidy Eligibility				
Subsidy Eligible * Yr 2014	-0.004*	0.000	0.019*	-0.019**
	(0.002)	(0.003)	(0.010)	(0.008)
Subsidy Eligible * Yr 2015	-0.014***	0.013***	0.035***	-0.045***
	(0.002)	(0.003)	(0.010)	(0.008)
Subsidy Eligible * Yr 2016	-0.019***	0.013***	0.025**	-0.034***
	(0.002)	(0.003)	(0.011)	(0.008)
Subsidy Eligible * Yr 2017	-0.020***	0.015***	-0.011	-0.000
	(0.002)	(0.003)	(0.011)	(0.009)
Policy Impacts				
Previously Eligible	0.023***	0.000	-0.016***	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Newly Eligible 2014	0.010	-0.034**	0.012	0.006
	(0.018)	(0.017)	(0.009)	(0.007)
Newly Eligible 2015	0.034*	-0.019	-0.016*	0.008
	(0.019)	(0.018)	(0.009)	(0.008)
Newly Eligible 2016	-0.045	0.057	0.043**	-0.064**
	(0.035)	(0.040)	(0.021)	(0.027)
Newly Eligible 2017	0.014	-0.008	-0.054**	0.063**
	(0.034)	(0.039)	(0.021)	(0.027)
Subsidy Eligible	-0.036***	-0.888***	0.556***	0.178***
	(0.002)	(0.003)	(0.010)	(0.006)
Observations	3,248,152	3,248,152	3,248,152	3,248,152

Notes: *** p<0.01, ** p<0.05, * p<0.10. Standard errors in parentheses and clustered at the PUMA level.The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

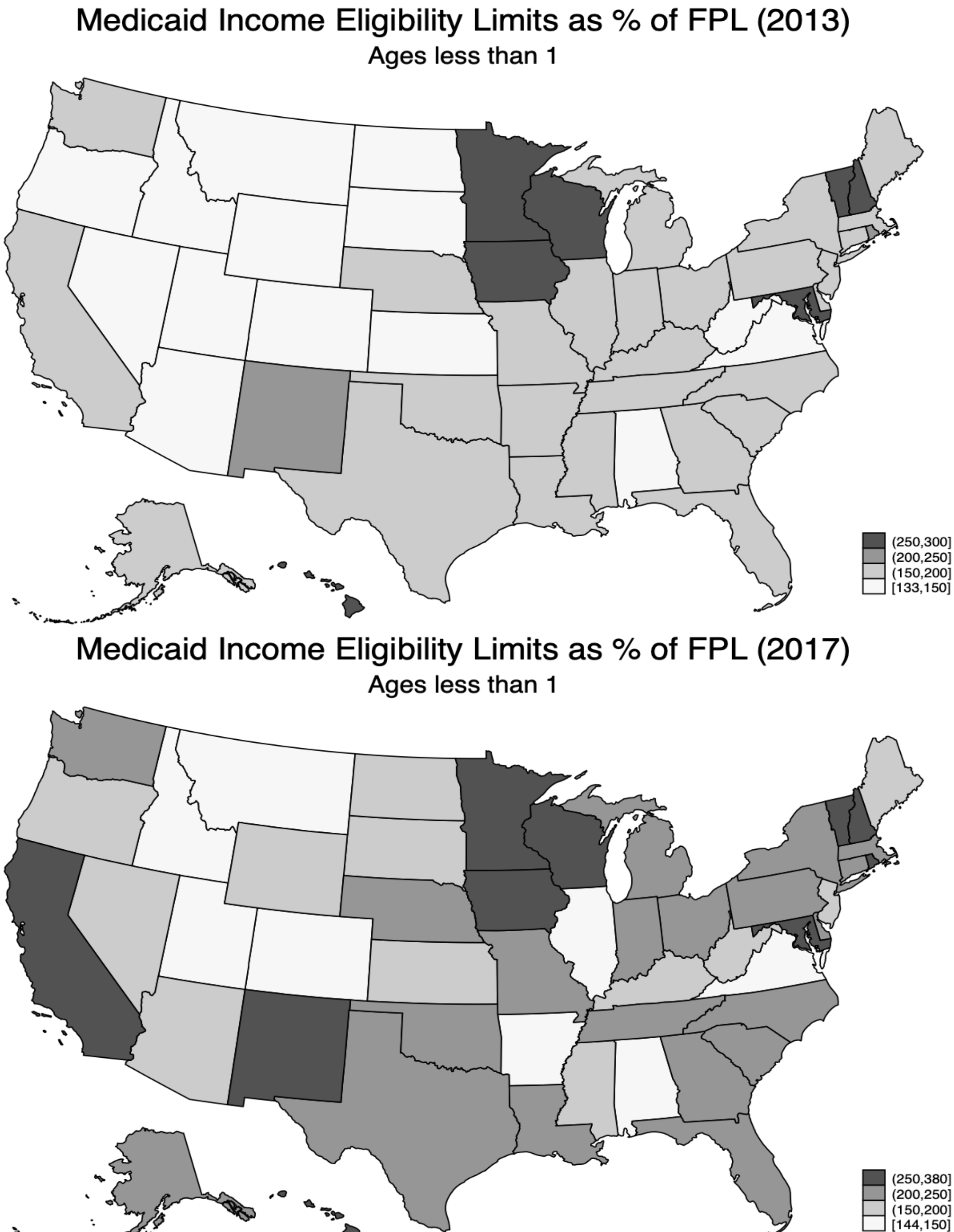
B.2 Figures

Figure B.1: ACA Medicaid Expansion Status (2014-2017)



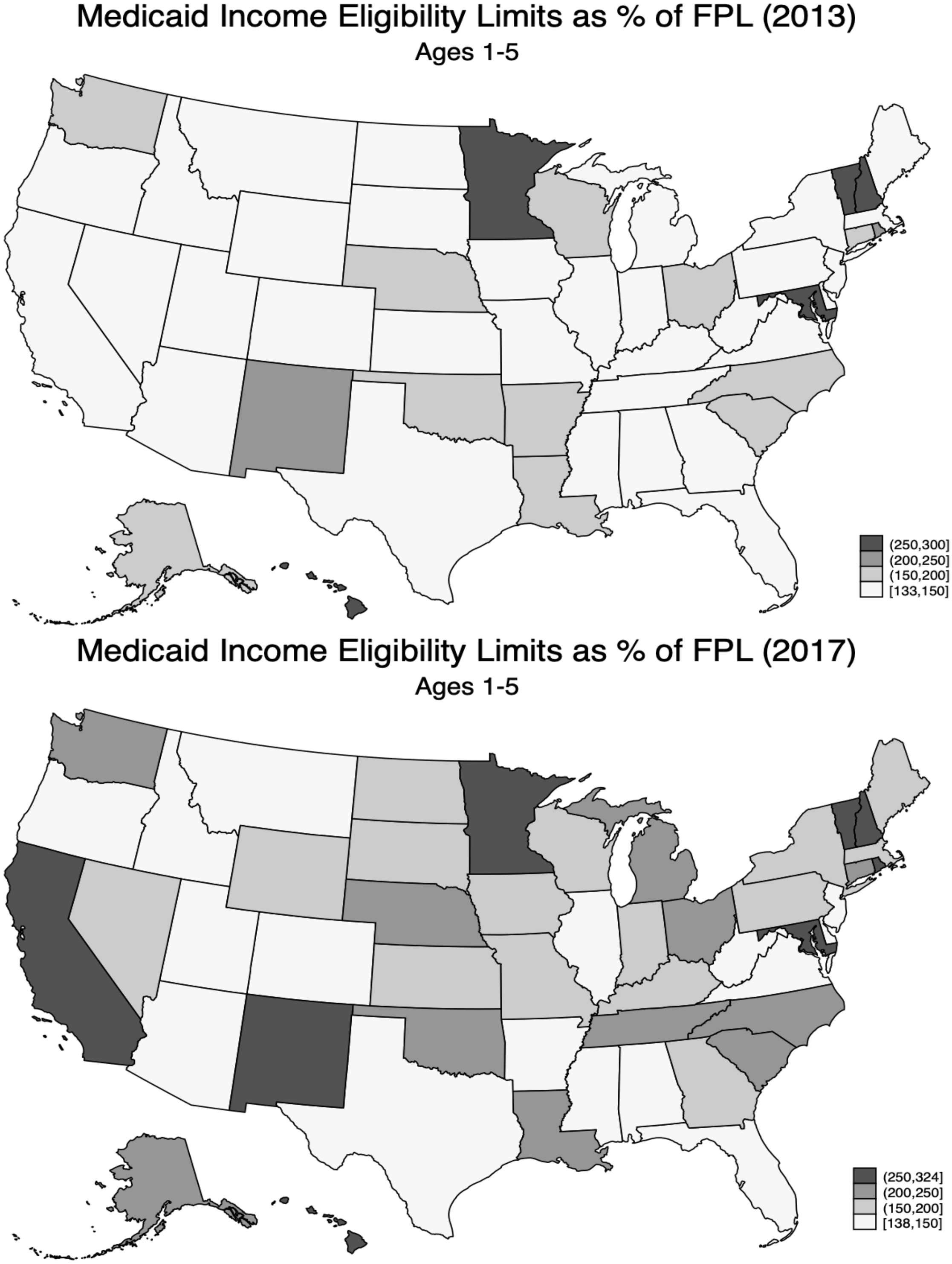
Notes: Figure was created by author using information on states' expansion status from the Kaiser Family Foundation (KFF).

Figure B.2: Medicaid Income Eligibility Limits as % of FPL (2013-2017): Ages < 1



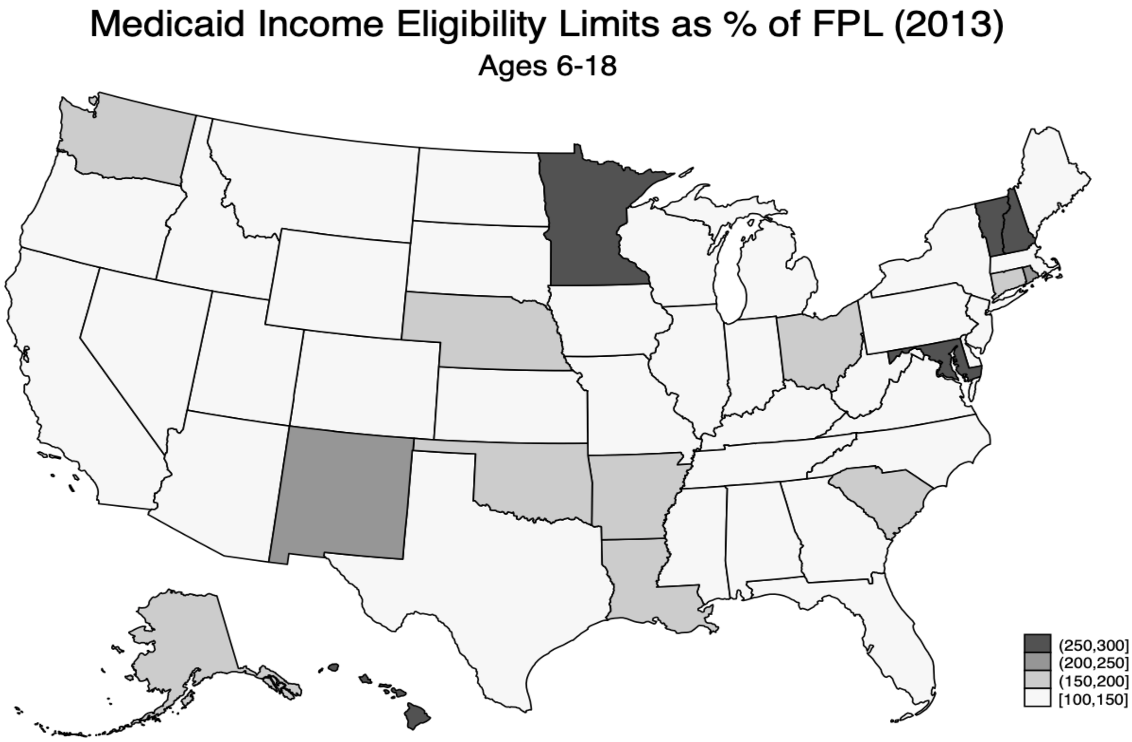
Note: Figure was created by author using information on states' Medicaid eligibility thresholds rates from the Kaiser Family Foundation (KFF).

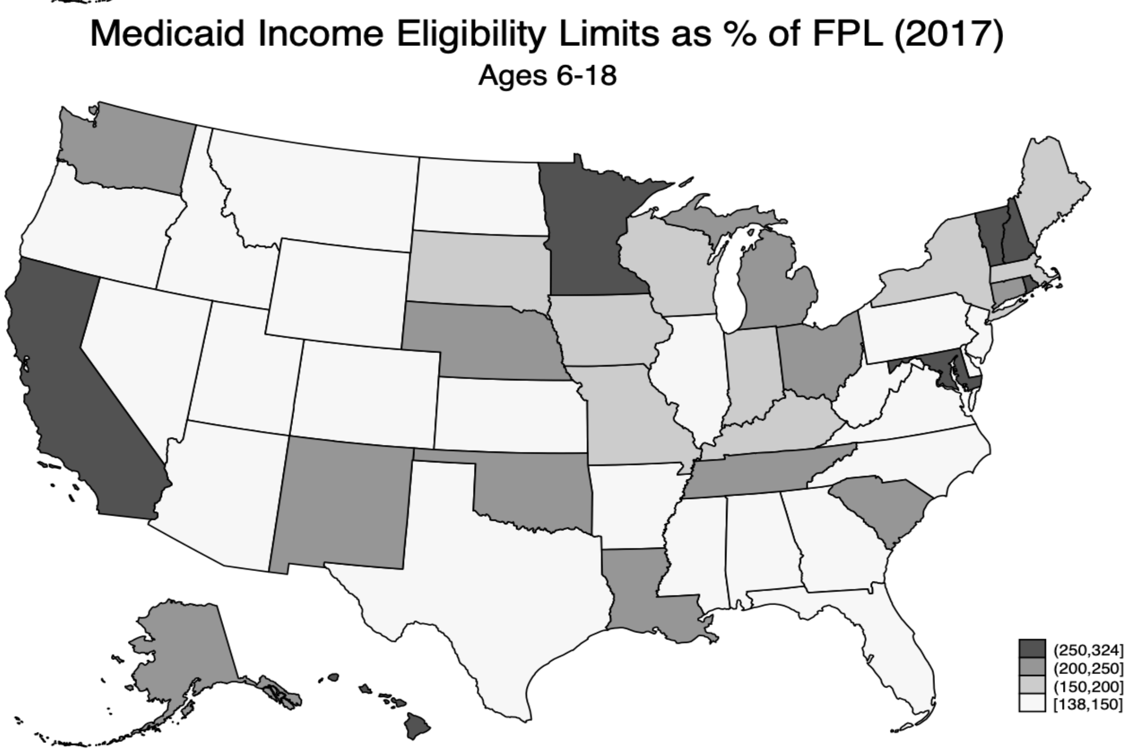
Figure B.3: Medicaid Income Eligibility Limits as % of FPL (2013-2017): Ages 1-5



Note: Figure was created by author using information on states' Medicaid eligibility thresholds rates from the Kaiser Family Foundation (KFF).

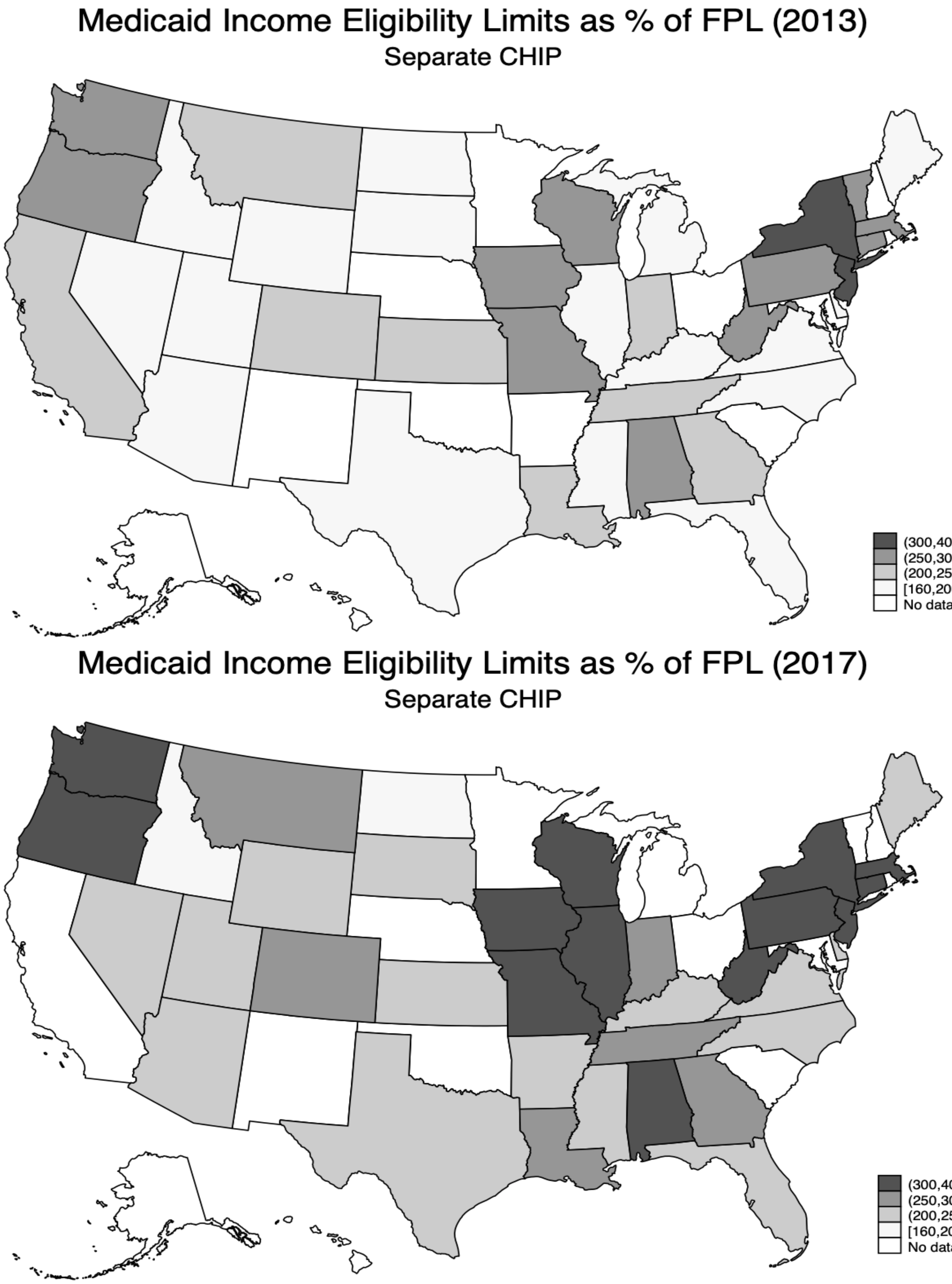
Figure B.4: Medicaid Income Eligibility Limits as % of FPL (2013-2017): Ages 6-18





Note: Figure was created by author using information on states' Medicaid eligibility thresholds rates from the Kaiser Family Foundation (KFF).

Figure B.5: Medicaid Income Eligibility Limits as % of FPL (2013-2017): Separate CHIP



Note: Figure was created by author using information on states' Medicaid eligibility thresholds rates from the Kaiser Family Foundation (KFF).

Literature Cited

Abadie, A. Bootstrap tests for distributional treatment effects in instrumental variable models. *Journal of the American statistical Association*, 97(457):284–292, 2002.

Abadie, A. Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics*, 113(2):231–263, 2003.

Abrigo, M. R., Halliday, T. J., and Molina, T. Expanding health insurance for the elderly of the philippines. *Journal of Applied Econometrics*, 2021.

Aizer, A. Public health insurance, program take-up, and child health. *The Review of Economics and Statistics*, 89(3):400–415, 2007.

Alker, J. and Corcoran, A. Children's uninsured rate rises by largest annual jump in more than a decade. *Washington, DC: Georgetown University Health Policy Institute, Center for Children and Families*, 2020.

Allen, H., Wright, B. J., Harding, K., and Broffman, L. The role of stigma in access to health care for the poor. *The Milbank Quarterly*, 92(2):289–318, 2014.

Andersen, R. M., Davidson, P. L., and Baumeister, S. E. Improving access to care in america. *Changing the US health care system: key issues in health services policy and management. 3a. edición. San Francisco: Jossey-Bass*, pages 3–31, 2007.

Angrist, J. D., Imbens, G. W., and Rubin, D. B. Identification of causal effects using instrumental variables. *Journal of the American statistical Association*, 91(434):444–455, 1996.

Applebaum, L. D. The influence of perceived deservingness on policy decisions regarding aid to the poor. *Political psychology*, 22(3):419–442, 2001.

Artiga, S., Ubri, P., Foutz, J., and Damico, A. Health coverage by race and ethnicity: Examining changes under the aca and the remaining uninsured. *Kaiser Family Foundation*, 2016.

Baicker, K., Taubman, S. L., Allen, H. L., Bernstein, M., Gruber, J. H., Newhouse, J. P., Schneider, E. C., Wright, B. J., Zaslavsky, A. M., and Finkelstein, A. N. The oregon experiment—effects of medicaid on clinical outcomes. *New England Journal of Medicine*, 368(18):1713–1722, 2013.

Batkins, S., Gitis, B., and Ryan, C. Obamacare's impact on small business wages and employment. In *American Action Forum*, 2014.

Bertrand, M., Duflo, E., and Mullainathan, S. How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, 119(1):249–275, 2004.

Brooks, T., Gardner, A., Tolbert, J., Dolan, R., and Pham, O. Medicaid and chip eligibility and enrollment policies as of january 2021: Findings from a 50-state survey. *Kaiser Family Foundation*, 8, 2021.

Brown-Iannuzzi, J. L., Dotsch, R., Cooley, E., and Payne, B. K. The relationship between mental representations of welfare recipients and attitudes toward welfare. *Psychological science*, 28(1):92–103, 2017.

Buettgens, M. and Kenney, G. M. *What if more states expanded Medicaid in 2017?: Changes in eligibility, enrollment, and the uninsured*. Urban Institute Washington (DC), 2016.

CMS. March 2021 medicaid & chip enrollment data highlights, 2021.

Courtemanche, C., Marton, J., and Yelowitz, A. Who gained insurance coverage in 2014, the first year of full aca implementation? *Health Economics*, 25(6):778–784, 2016.

Courtemanche, C., Marton, J., Ukert, B., Yelowitz, A., and Zapata, D. Early impacts of the affordable care act on health insurance coverage in medicaid expansion and non-expansion states. *Journal of Policy Analysis and Management*, 36(1):178–210, 2017.

Courtemanche, C., Marton, J., Ukert, B., Yelowitz, A., Zapata, D., and Fazlul, I. The three-year impact of the affordable care act on disparities in insurance coverage. *Health services research*, 54:307–316, 2019.

Currie, J. and Gruber, J. Health insurance eligibility, utilization of medical care, and child health. *The Quarterly Journal of Economics*, 111(2):431–466, 1996a.

Currie, J. and Gruber, J. Saving babies: The efficacy and cost of recent changes in the medicaid eligibility of pregnant women. *Journal of political Economy*, 104(6):1263–1296, 1996b.

Cutler, D. M. and Gruber, J. Does public insurance crowd out private insurance? *The Quarterly Journal of Economics*, 111(2):391–430, 1996.

Decker, S. L., Lipton, B. J., and Sommers, B. D. Medicaid expansion coverage effects grew in 2015 with continued improvements in coverage quality. *Health affairs*, 36(5):819–825, 2017.

DeNavas-Walt, C., Proctor, B. D., and Smith, J. C. Income, poverty, and health insurance coverage in the united states: 2012. current population reports p60-245. *US Census Bureau*, 2013.

Dubay, L. and Kenney, G. M. When the chips are down—health coverage and care at risk for us children. *New England Journal of Medicine*, 378(7):597–599, 2018.

Duggan, M., Goda, G. S., and Jackson, E. The effects of the affordable care act on health insurance coverage and labor market outcomes. *National Tax Journal*, 72(2):261–322, 2019.

Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J. P., Allen, H., Baicker, K., and Group, O. H. S. The oregon health insurance experiment: evidence from the first year. *The Quarterly journal of economics*, 127(3):1057–1106, 2012.

Frean, M., Gruber, J., and Sommers, B. D. Premium subsidies, the mandate, and medicaid expansion: Coverage effects of the affordable care act. *Journal of Health Economics*, 53: 72–86, 2017.

Gallen, T. S. and Mulligan, C. B. Wedges, labor market behavior, and health insurance coverage under the affordable care act. Technical report, National Bureau of Economic Research, 2013.

Gans, H. J. *The War against the Poor. The Underclass and Antipoverty Policy.* ERIC, 1995.

Garfield, R., Orgera, K., and Damico, A. The coverage gap: Uninsured poor adults in states that do not expand medicaid. kff, 2021.

Garrett, A. B., Kaestner, R., and Gangopadhyaya, A. Recent evidence on the aca and employment: Has the aca been a job killer? 2016 update. *The Urban Institute, ACA Implementation—Monitoring and Tracking*, 2017.

Georgetown University Center for Children and Families. The maintenance of effort (moe) provision in the affordable care act. https://ccf.georgetown.edu/wp-content/uploads/2017/05/ MOE-fact-sheet-FINAL.pdf, 2017.

Goodman-Bacon, A. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277, 2021.

Goodman-Bacon, A., Goldring, T., and Nichols, A. Bacondecomp: Stata module to perform a bacon decomposition of difference-in-differences estimation. 2019.

Gooptu, A., Moriya, A. S., Simon, K. I., and Sommers, B. D. Medicaid expansion did not result in significant employment changes or job reductions in 2014. *Health affairs*, 35(1): 111–118, 2016.

Grogan, C. M. and Park, S. The racial divide in state medicaid expansions. *Journal of Health Politics, Policy and Law*, 42(3):539–572, 2017.

Gruber, J. The impacts of the affordable care act: how reasonable are the projections? *National Tax Journal*, 64(3):893–908, 2011.

Haley, J. M., Kenney, G. M., Pan, C. W., Wang, R., Lynch, V., and Buettgens, M. Uninsurance rose among children and parents in 2019. *Washington, DC: Urban Institute, July*, 15, 2021.

Halliday, T. J. and Akee, R. Q. The impact of medicaid on medical utilization in a vulnerable population: evidence from cofa migrants. *Health Economics*, 29(10):1231–1250, 2020.

Hamersma, S., Kim, M., and Timpe, B. The effect of parental medicaid expansions on children's health insurance coverage. *Contemporary Economic Policy*, 37(2):297–311, 2019.

Heckman, J. J. and Vytlacil, E. J. Local instrumental variables and latent variable models for identifying and bounding treatment effects. *Proceedings of the national Academy of Sciences*, 96(8):4730–4734, 1999.

Hudson, J. L. and Moriya, A. S. Medicaid expansion for adults had measurable 'welcome mat'effects on their children. *Health affairs*, 36(9):1643–1651, 2017.

Imbens, G. W. and Rubin, D. B. Estimating outcome distributions for compliers in instrumental variables models. *The Review of Economic Studies*, 64(4):555–574, 1997.

Kaestner, R., Garrett, B., Chen, J., Gangopadhyaya, A., and Fleming, C. Effects of aca medicaid expansions on health insurance coverage and labor supply. *Journal of Policy Analysis and Management*, 36(3):608–642, 2017.

Kaiser Family Foundation. Health coverage of immigrants. https://www.kff.org/racial-equity-and-health-policy/fact-sheet/health-coverage-of-immigrants/, 2021.

Kaiser Family Foundation. Medicaid waiver tracker: Approved and pending section 1115 waivers by state. https://www.kff.org/medicaid/issue-brief/medicaid-waiver-tracker-approved-and-pending-section-1115-waivers-by-state/, 2022a.

Kaiser Family Foundation. Medicaid income eligibility limits for adults as a percent of the federal poverty level. https://www.kff.org/medicaid/state-indicator/medicaid-income-eligibility-limits-for-other-non-disabled-adults/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D, 2022b.

Katz, L. F., Kling, J. R., and Liebman, J. B. Moving to opportunity in boston: Early results of a randomized mobility experiment. *The quarterly journal of economics*, 116(2):607–654, 2001.

Ko, H., Howland, R. E., and Glied, S. A. The effects of income on children's health: Evidence from supplemental security income eligibility under new york state medicaid. Technical report, National Bureau of Economic Research, 2020.

Kowalski, A. E. Doing more when you're running late: Applying marginal treatment effect methods to examine treatment effect heterogeneity in experiments. Technical report, National Bureau of Economic Research, 2016.

Layton, T. J., Montz, E., and Shepard, M. Health plan payment in us marketplaces: regulated competition with a weak mandate. In *Risk Adjustment, Risk Sharing and Premium Regulation in Health Insurance Markets*, pages 491–522. Elsevier, 2018.

Lee, H. and Porell, F. W. The effect of the affordable care act medicaid expansion on disparities in access to care and health status. *Medical Care Research and Review*, 77(5): 461–473, 2020.

Leung, P. and Mas, A. Employment effects of the affordable care act medicaid expansions. *Industrial Relations: A Journal of Economy and Society*, 57(2):206–234, 2018.

Lino, M., Kuczynski, K., Rodriguez, N., and Schap, T. *Expenditures on children by families, 2015*. Center for Nutrition Policy and Promotion, US Department of Agriculture, 2017.

Mach, A. and O'Hara, B. Do people really have multiple health insurance plans? estimates of nongroup health insurance in the american community survey. *Washington, DC: US Census Bureau. Accessed April*, 10:2013, 2011.

Medicaid and CHIP Payment and Access Commission (MACPAC). Racial and ethnic disparities in medicaid: An annotated bibliography. https://www.macpac.gov/wp-content/uploads/2021/04/Racial-and-Ethnic-Disparities-in-Medicaid-An-Annotated-Bibliography.pdf, 2021.

Michener, J. Race, politics, and the affordable care act. *Journal of Health Politics, Policy and Law*, 45(4):547–566, 2020.

Miller, S. and Wherry, L. R. Health and access to care during the first 2 years of the aca medicaid expansions. *New England Journal of Medicine*, 376(10):947–956, 2017.

Miller, S., Johnson, N., and Wherry, L. R. Medicaid and mortality: new evidence from linked survey and administrative data. *The Quarterly Journal of Economics*, 136(3):1783–1829, 2021.

Moffitt, R. A. The deserving poor, the family, and the us welfare system. *Demography*, 52 (3):729–749, 2015.

Moriya, A. S., Selden, T. M., and Simon, K. I. Little change seen in part-time employment as a result of the affordable care act. *Health affairs*, 35(1):119–123, 2016.

Mulligan, C. B. The employer penalty, voluntary compliance, and the size distribution of firms: Evidence from a survey of small businesses. *Tax Policy and the Economy*, 34(1): 139–171, 2020.

Pascale, J., Call, K., Fertig, A., and Oellerich, D. Validating self-reported health insurance coverage: preliminary results on cps and acs. *Washington, DC: United States Census Bureau*, 2016.

Simon, K., Soni, A., and Cawley, J. The impact of health insurance on preventive care and health behaviors: evidence from the first two years of the aca medicaid expansions. *Journal of Policy Analysis and Management*, 36(2):390–417, 2017.

Somers, S. A., Hamblin, A., Verdier, J. M., Byrd, V. L., et al. Covering low-income childless adults in medicaid: Experiences from selected states. Technical report, Mathematica Policy Research, 2010.

Sommers, B. D., Tomasi, M. R., Swartz, K., and Epstein, A. M. Reasons for the wide variation in medicaid participation rates among states hold lessons for coverage expansion in 2014. *Health affairs*, 31(5):909–919, 2012.

Sommers, B. D., Arntson, E., Kenney, G. M., and Epstein, A. M. Lessons from early medicaid expansions under health reform: interviews with medicaid officials. *Medicare & medicaid research review*, 3(4), 2013.

Sommers, B. D., Gunja, M. Z., Finegold, K., and Musco, T. Changes in self-reported insurance coverage, access to care, and health under the affordable care act. *Jama*, 314 (4):366–374, 2015.

Sommers, B. D., Gawande, A. A., and Baicker, K. Health insurance coverage and health—what the recent evidence tells us, 2017.

Sommers, B. D., Goldman, A. L., Blendon, R. J., Orav, E. J., and Epstein, A. M. Medicaid work requirements—results from the first year in arkansas. *New England Journal of Medicine*, 381(11):1073–1082, 2019.

Stuber, J. P., Maloy, K. A., Rosenbaum, S., and Jones, K. C. Beyond stigma: What barriers actually affect the decisions of low-income families to enroll in medicaid? 2000.

Sun, L. Eventstudyweights: Stata module to estimate the implied weights on the cohort-specific average treatment effects on the treated (catts)(event study specifications). 2021.

Sun, L. and Abraham, S. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199, 2021.

Weech-Maldonado, R., Morales, L. S., Elliott, M., Spritzer, K., Marshall, G., and Hays, R. D. Race/ethnicity, language, and patients' assessments of care in medicaid managed care. *Health services research*, 38(3):789–808, 2003.

Wherry, L. R. and Miller, S. Early coverage, access, utilization, and health effects associated with the affordable care act medicaid expansions: a quasi-experimental study. *Annals of internal medicine*, 164(12):795–803, 2016.