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

Benjamin C. Chu[‡]

University of Hawai'i at Mānoa

January 27, 2023

[†]The views presented are those of the author. This paper also uses data from the American Community Survey (ACS) and can be obtained directly from the Census Bureau File Transfer Protocol (FTP) site (https://www2.census.gov/programs-surveys/acs/data/pums/). I thank Timothy Halliday, Teresa Molina, Dylan Moore, Sang Hyop Lee, Ruben Juarez, Victoria Fan and participants at the UH Mānoa Applied Microeconomics Seminar for excellent comments and feedback that have contributed to the progress of this paper. I have not received any funding for this project. All errors are my own. Declaration of Interests: none

[‡]Doctoral Candidate, University of Hawai'i at Mānoa. Address: 2424 Maile Way, 525 Saunders Hall, Honolulu, HI 96822. email: bcchu@hawaii.edu

Abstract

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.

Keywords: Medicaid, ACA, Expansion, Complier JEL Classifications: I13, I30

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 have 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. TThis 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. 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). I then estimate a saturated probit model and utilize methods from Abadie (2003) to derive the probability of being a complier by race/ethnicity and work status. I also estimate the likelihood of being 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)

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

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.

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 have the highest likelihood of being a complier across all work groups and states. Broken down by race/ethnicity, I discover that Black individuals are more likely to be compliers in non-expansion states than other racial/ethnic groups, many of which have 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

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

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

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, 2016). None of these studies, however, estimate 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 2 provides a brief overview of the ACA Medicaid expansion. Sections 3 and 4 discuss the data and empirical design used in this study. Section 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 6 discusses the policy implications and concludes.

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, 2022, 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 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

[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 A1 in the appendix maps each state's expansion status from 2014-2017.

[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).

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 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 A2 in the appendix summarizes the changes in the mean Medicaid eligibility thresholds by state between 2013 and 2014.

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

[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.

3 Data

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 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, 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

[11] The Census is unable to determine poverty status for people in military barracks, college dormitories, institutional group quarters, or in living situations without conventional housing.

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 allows 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 exclude 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 exclude 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 restrict my sample to individuals that meet the following criteria: aged between 26 and 64, childless, non-disabled, and with incomes below 138% of the FPL. I impose 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 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.

[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.

3.2 Summary Statistics

Table 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 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.

4 Empirical Methodology

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,

[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

it corresponds to having Medicaid coverage. Treatment status is determined by a latent variable of the form:

$$I = p_z - U \tag{1}$$

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 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, 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]

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.

[18]The never takers could also consist of individuals who opted not to enroll in Medicaid due to being

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 violators 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 int he 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 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:

$$\begin{aligned} \mu_x(0) &= E(X \mid D = 0, p_0 \leq U < p_1) = E(X \mid Z = 0, p_0 \leq U < p_1) \\ &= \frac{1}{(p_1 - p_0)} \left[E(X \mid Z = 0, D = 0)\,(1 - p_0) - E(X \mid Z = 1, D = 0)\,(1 - p_1) \right] \end{aligned} \tag{2}$$

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:

$$\begin{aligned} \mu_x(1) &= E(X \mid D = 1, p_0 \leq U < p_1) = E(X \mid Z = 1, p_0 \leq U < p_1) \\ &= \frac{1}{(p_1 - p_0)} \left[E(X \mid Z = 1, D = 1)\,p_1 - E(X \mid Z = 0, D = 1)\,p_0 \right] \end{aligned} \tag{3}$$

where ATTC represents the combination of the always takers and the treated compliers. The benefits of treatment p_1 and p_0 in equations (2) and (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 4.3. To derive the average characteristics of the compliers, I take the weighted sum of the solutions to equations (2) and (3).[19]

covered under ESI or non-group private coverage.

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

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:

$$X_{ist} = \lambda_{NT} + \lambda_{AT}\,1(AT_{ist}) + \lambda_{AT+TC}\,1(ATTC_{ist}) + \lambda_{NT+UC}\,1(NTUC_{ist}) + \gamma_t + \phi_s + u_{ist} \quad (4)$$

The conditional expectations required to estimate the expectations in equations (2) and (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 (2) and serves as the constant or intercept in the regression. Similarly, λ_{AT} estimates $E(X|Z=0, D=1)$ in equation (3), λ_{AT+TC} estimates $E(X|Z=1, D=1)$ in equation (3), and λ_{NT+UC} estimates $E(X|Z=0, D=0)$ in equation (2). I include year (γ_t) and state (ϕ_s) fixed effects to control for differences across states and time.

4.3 Difference-in-Differences

4.3.1 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:

$$D_{ist} = \beta_0 + \beta_1 Z_{st} + \beta_2 X_{ist} + \gamma_t + \phi_s + \epsilon_{ist} \quad (5)$$

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.

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 (5) are the propensity scores that correspond to the benefits of treatments described in section 4.1 and are used to solve for the average characteristics of the treated and untreated compliers in equations (2) and (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.

4.3.2 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.

[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 specification for the event study is as follows:

$$D_{ist} = Z_{st} \times \sum_{\substack{y=-4 \\ y\neq -1}}^{3} \beta_y I(t - t_s^* = y) + \beta_x X_{ist} + \gamma_t + \phi_s + \epsilon_{ist} \tag{6}$$

where y is equal to the difference between the year observed and treatment period for state s. The indicator terms $I(t - t_s^* = y)$ 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 $y < 1$ is close to zero and statistically insignificant, then the parallel trends assumption holds. I estimate equation (6) using a linear probability model with ACS survey weights and cluster the standard errors at the state level.[22]

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):

[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.

[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 B in the appendix using the techniques introduced in these studies to evaluate whether staggered treatment is a concern in my design. Figure B1 reports my results using the methods from Sun and Abraham (2021), while figure B2 and table B1 report those from Goodman-Bacon (2021).

$$
\begin{aligned}
Pr(p_0 \leq U < p_1 \mid X) &= 1 - Pr(D=0 \mid X) - Pr(D=1 \mid X) \\
&= \underbrace{1 - Pr(D=0 \mid Z=1, X)}_{=p_1} - \underbrace{Pr(D=1 \mid Z=0, X)}_{=p_0} \\
&= \underbrace{Pr(D=1 \mid Z=1, X)}_{=p_1} - \underbrace{Pr(D=1 \mid Z=0, X)}_{=p_0}
\end{aligned}
\tag{7}
$$

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 (7). As outlined in figure 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 (5) only provides the unconditional estimates of p_1 and p_0. Therefore, I modify equation (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 variable of interest. Then, I apply equation (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 (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

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

[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.

cannot be fully explained by traditional difference-in-differences methods alone, i.e., equation (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 (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 (4). Third, I utilize the estimates from the previous steps alongside equations (2) and (3) to calculate the conditional expectations of the compliers with the optimal weights. Finally, I run a saturated probit model in equation and apply equation (7) to estimate the probability of being a complier at both the aggregate and state-level.

5 Results

5.1 Estimating the Probability of Medicaid Take-up

In Table 3, I provide the results from the DID regression in equation (5) on the effects of the ACA Medicaid expansion on health coverage. Columns (1) - (4) provide the 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, $Z_{st} = POST_t \times Expand_s$.

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 are 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 (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 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.

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 (5), I observe negative and statistically significant changes in private coverage and the uninsured rate.

[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 A1 in the appendix.

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 the equation 4. As stated in section 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 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 A3 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 3, the compliers were primarily part-time workers as the means of the compliers for part-time workers are above those of the never takers and always takers. Those who do not work are disproportionately always takers, whereas full-time workers are 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 are disproportionately always takers, as the means of the compliers are above those of the never takers, but below those of the always takers. Hispanics are disproportionately never takers, as the means of the compliers are 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

[27] Tabulated versions of these figures are reported in tables A2 in the appendix.

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 are disproportionately White, the always takers are disproportionately Black, and the never takers are 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).

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 4. I also provide the results for income group and education in figure A4 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 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

[28] This pattern is also consistent with education, as shown in figure A3.

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 3.

In the right panel, there are no discernible differences in the probability of being a complier by race/ethnicity. This contrasts with the conditional means presented in figure 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 3 that the compliers were disproportionately White, this is not the case in figure 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 are the most likely to be always takers and the least likely to be never takers, which is consistent with figure 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 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 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 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 A5 where the probability of being an always taker is higher in these states, whereas figure A6 shows that the probability of being

[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 2, this could explain why they are also highly likely to be never takers.

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

I present the state-level complier probabilities for race/ethnicity in figure 3. Figures A7 and A8 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 10 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 9 of them, with the exception of Wyoming (WY). It is important to note that in these 9 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 10 states (AL, AR, DE, GA, LA, MD, MS, NC, SC, VA) with the highest Black populations, the complier probabilities are higher for Blacks compared to Whites in 7 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.

[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 A3 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.

[32]I report the differences in the complier probabilities for Blacks and Whites for these in table A4 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.

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 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 point to potential racial/ethnic biases that hinder 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. Furthermore, this paper is 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.

References

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.

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.

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.

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.

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.

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.

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.

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.

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.

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. 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.

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.

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.

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.

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.

Table 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 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

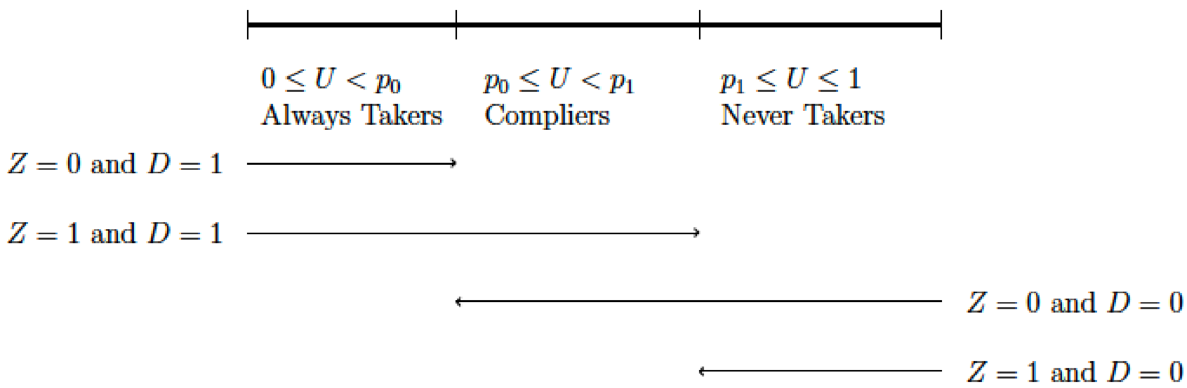
Table 3: The Effects the ACA Medicaid Expansion on Health Insurance Coverage for Childless Adults

	(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 (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.

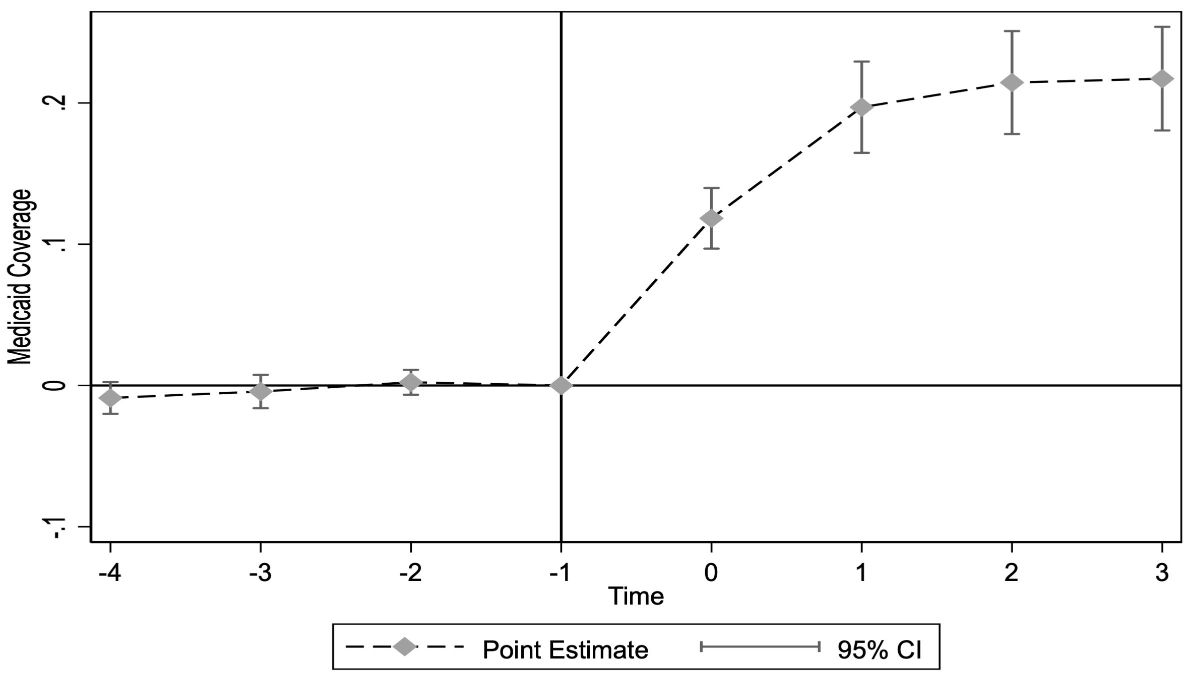
Figure 1: Treatment Groups from Complier Analysis

Figure.png



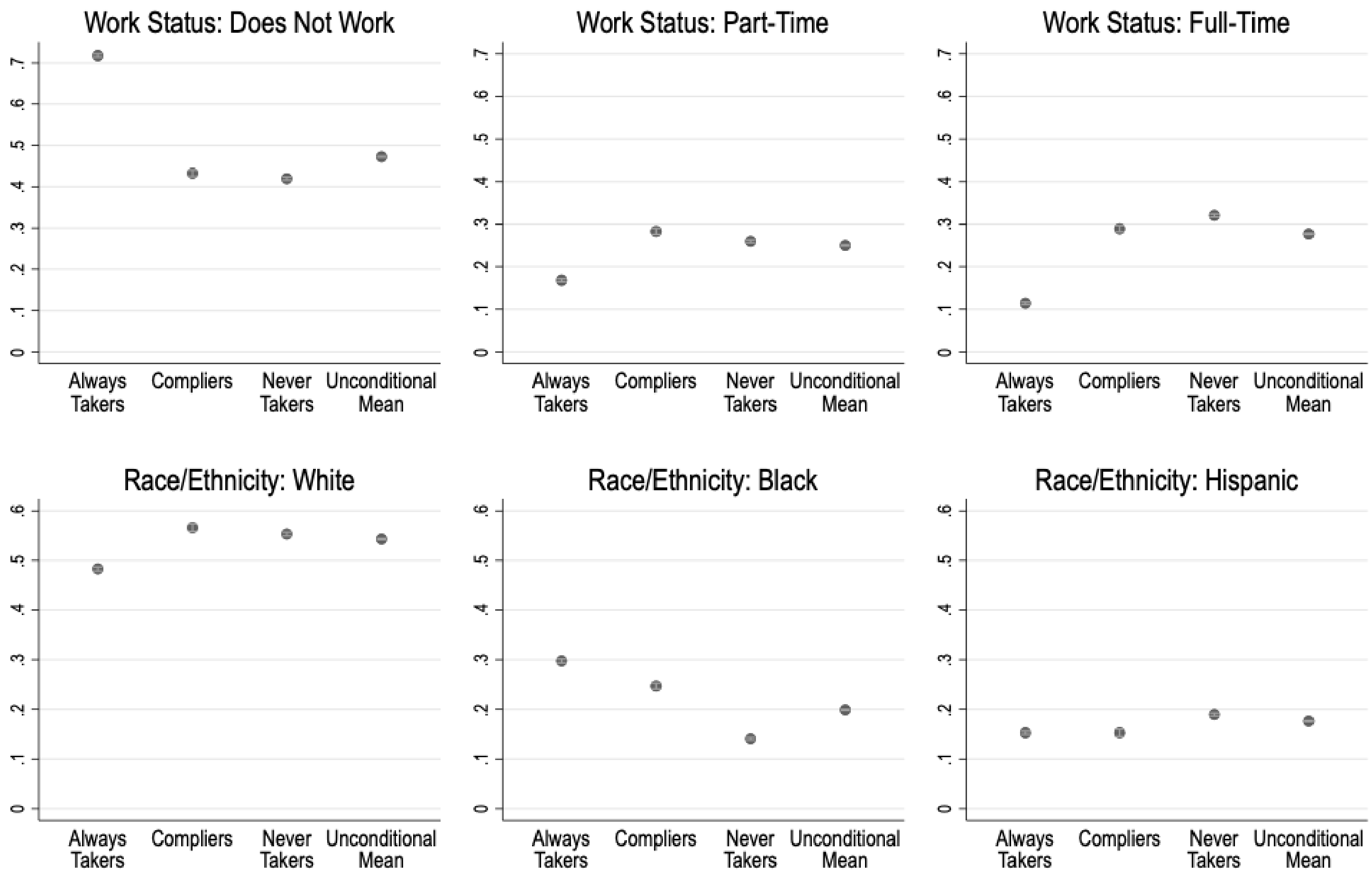
Source: Abrigo et al. (2021)

Figure 2: Event Study of the ACA Medicaid Expansion (2010-2017)



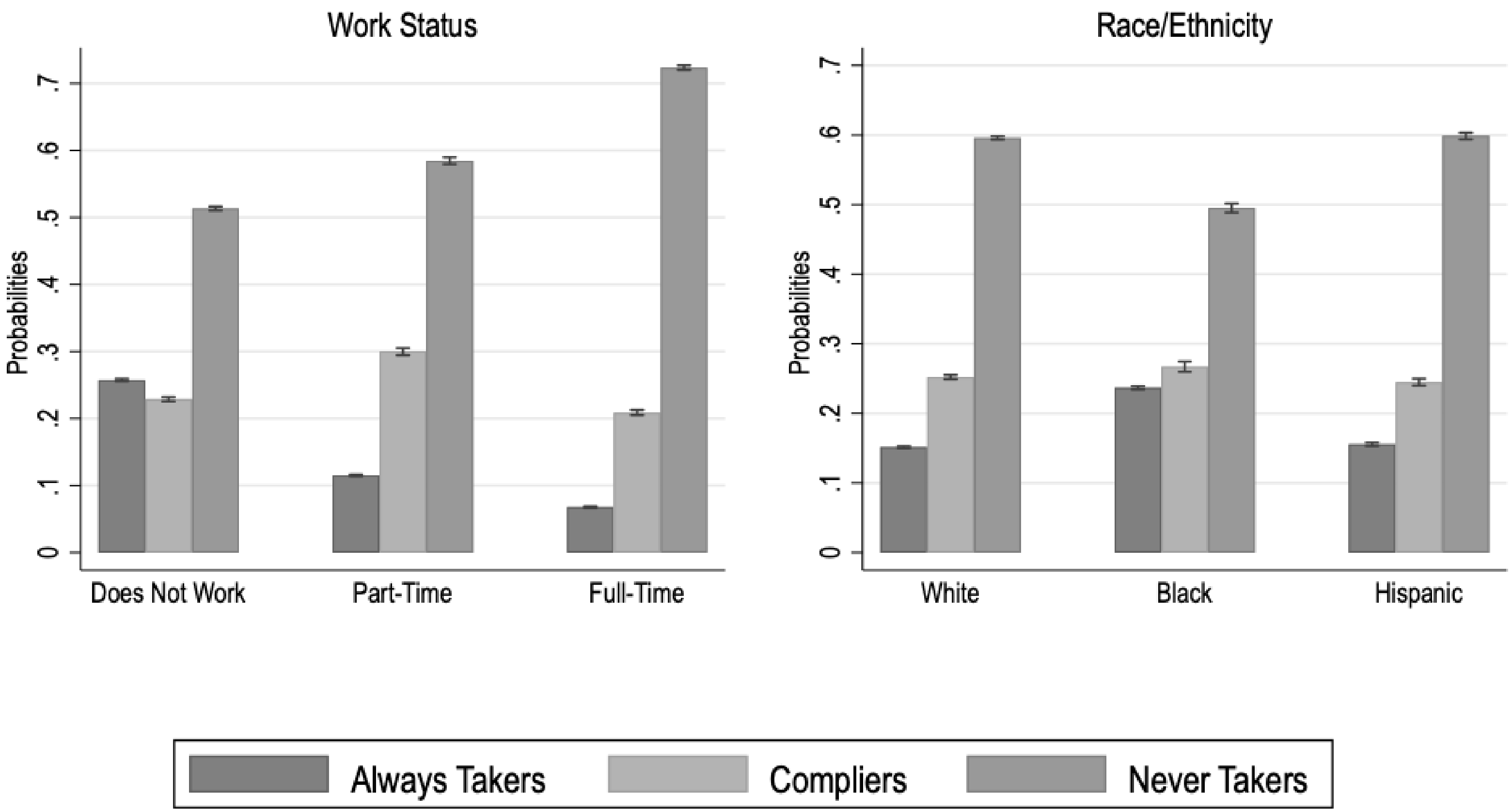
Notes: This figure reports the coefficients from estimating equation (6) with Medicaid coverage as the outcome variable. The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% of the FPL. Controls include gender, race/ethnicity, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates are weighted using ACS weights.

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



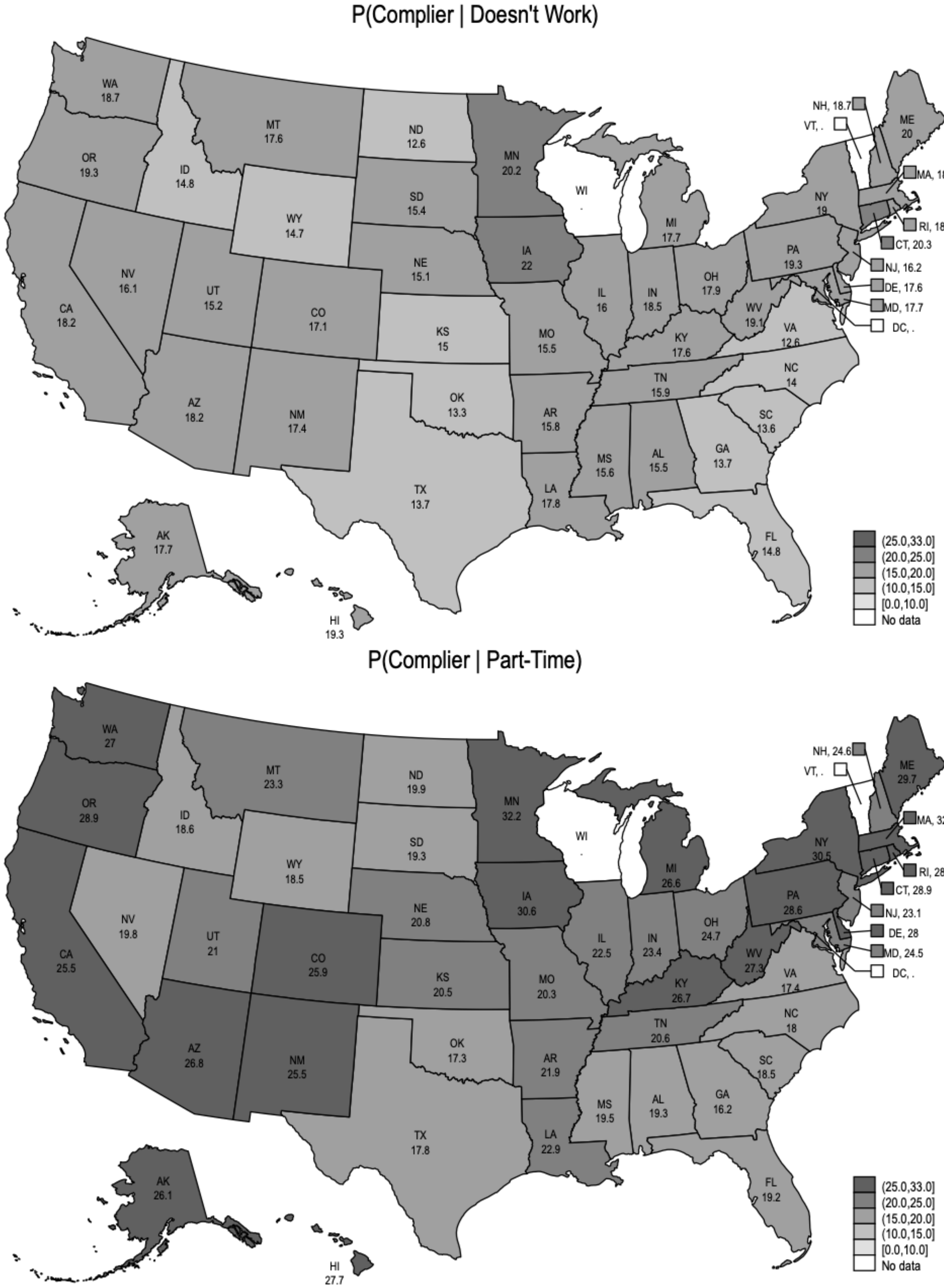
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

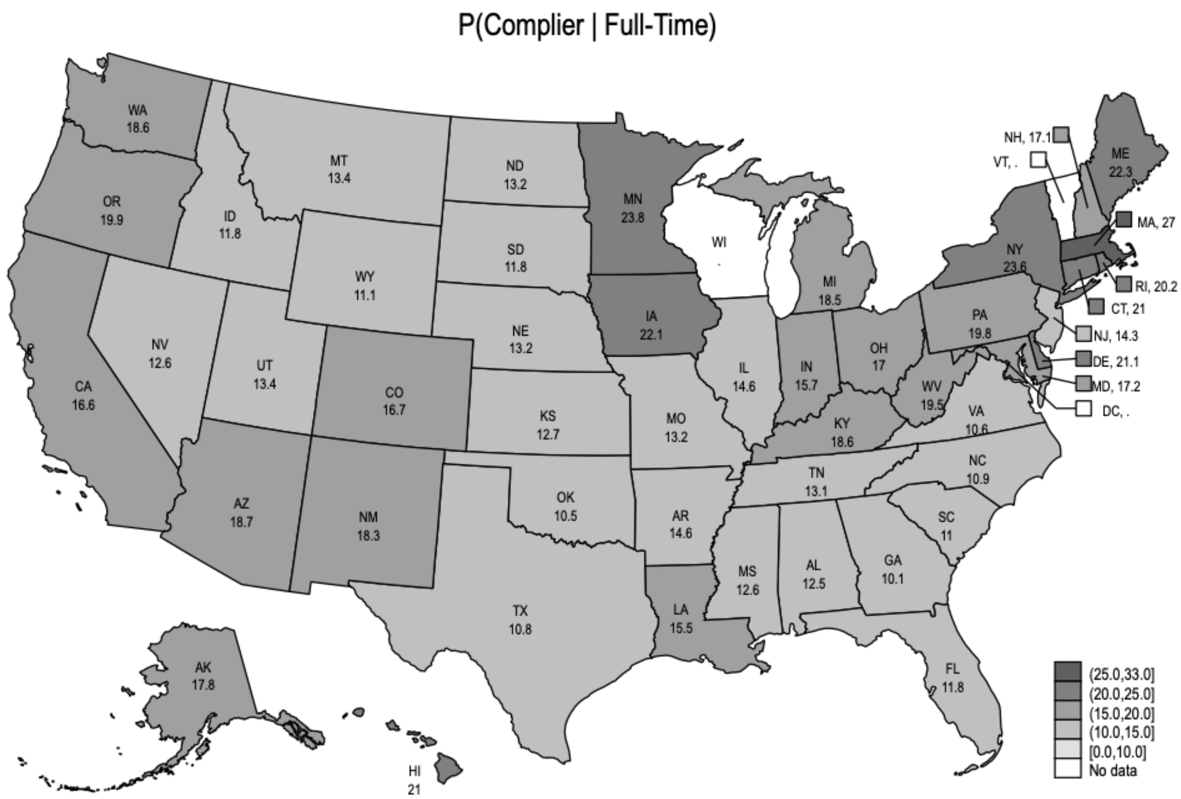
Figure 4: Conditional Probabilities of the Always Takers, Compliers, and Never Takers: Work Status and Race/Ethnicity, Childless Adults (0-138% FPL)



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

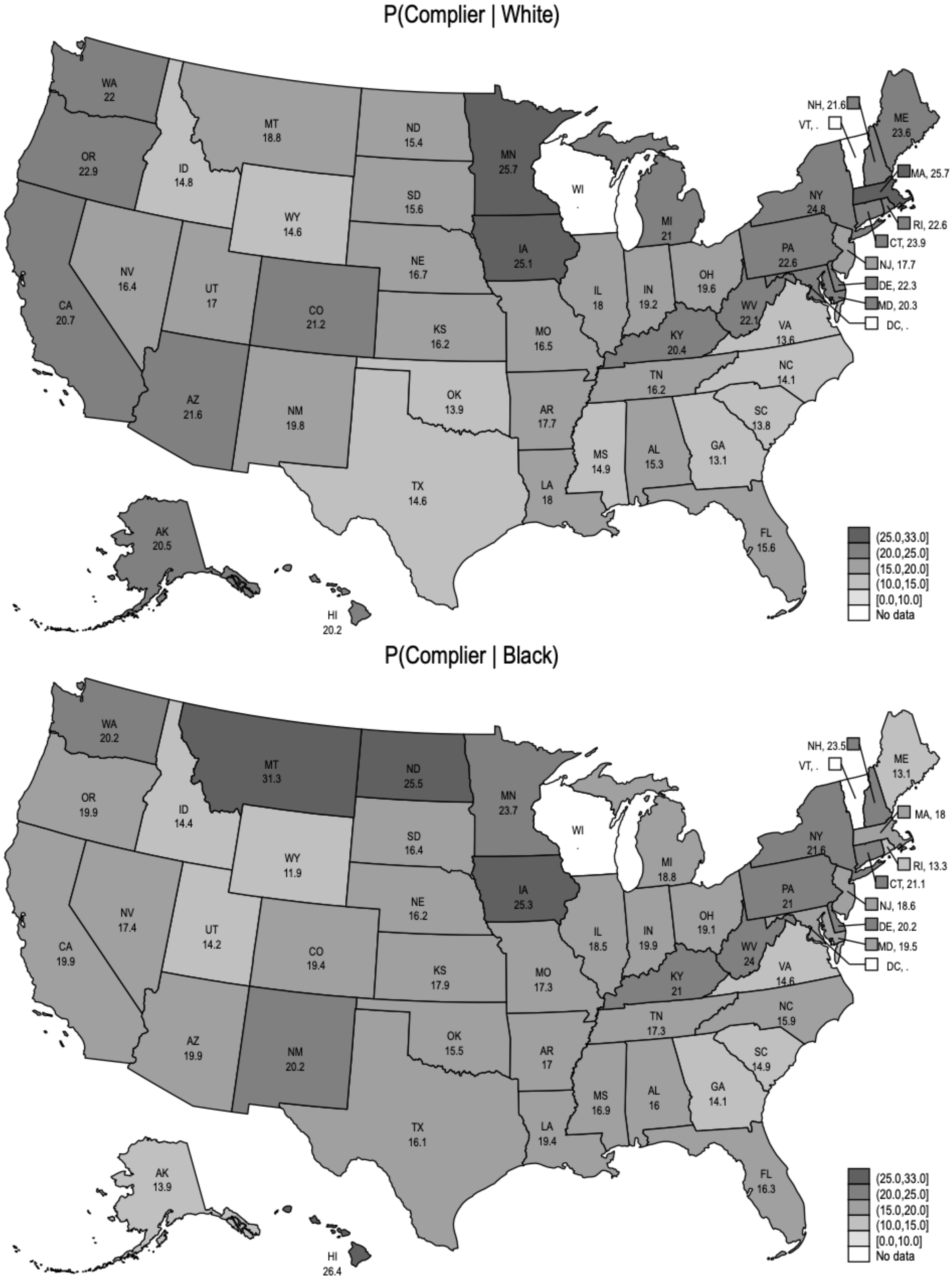
Figure 5: State-Level Conditional Probabilities of the Compliers: Work Status, Childless Adults (0-138% FPL)

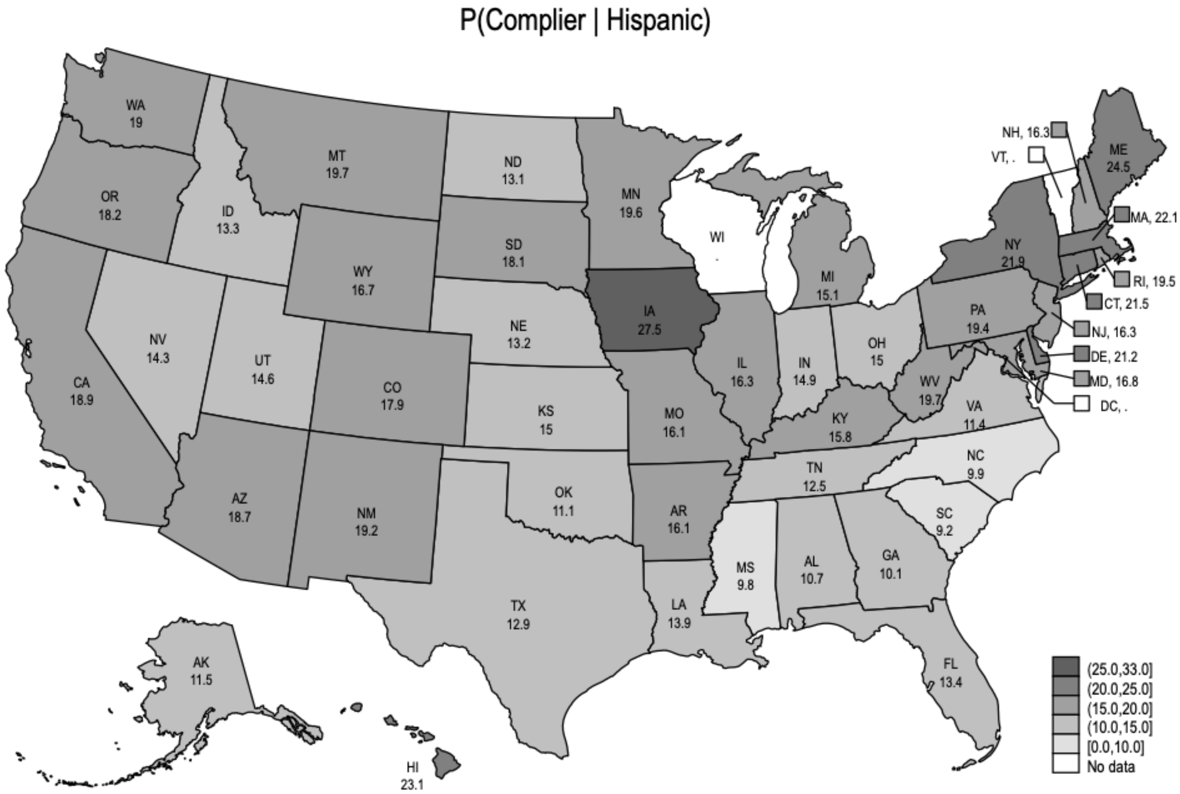




Notes: I report the estimates on the probability of being a complier for each state using a saturated probit model and methods from Abadie (2003). These include counterfactual estimates for non-expansion states or the probability of being a complier if that state had expanded Medicaid in 2014. Estimates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

Figure 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.

Appendix A Tables and Figures

Table A1: 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 (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 A2: 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 A3: Conditional Probability of Being a Complier in Non-Expansion States (0-138% FPL)

	(1) $P(C \mid Black)$	(2) $P(C \mid White)$	(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%

Notes: I present estimates of the conditional probability of being a complier for White and Black childless adults in states that have not chosen to expand Medicaid by January 1st, 2023. The standard errors are reported in parentheses and were estimated from 1000 bootstrapped re-samples. Note that Wisconsin (WI) did not participate in the ACA expansion, but is omitted from my results due to expanding Medicaid to those below 100% of the FPL. In addition to the complier probabilities, I also report 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.

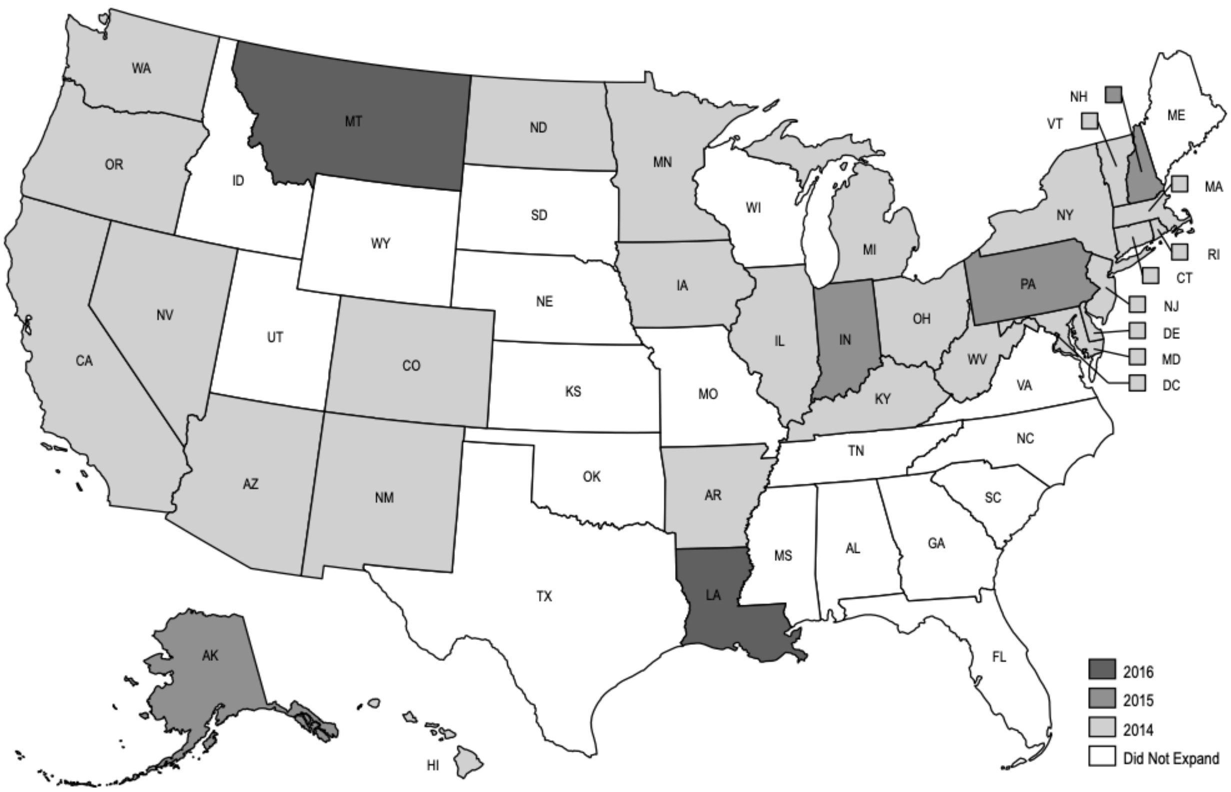
Table A4: Conditional Probability of Being a Complier in the Top Ten States with the Highest Percentage of Black Childless Adults (0-138% FPL)

	(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

Notes: I present estimates of the conditional probability of being a complier for White and Black childless adults in the 10 states with the highest proportion of Black people. The standard errors are reported in parentheses and were estimated from 1000 bootstrapped re-samples. In addition to the complier probabilities, I also report 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.

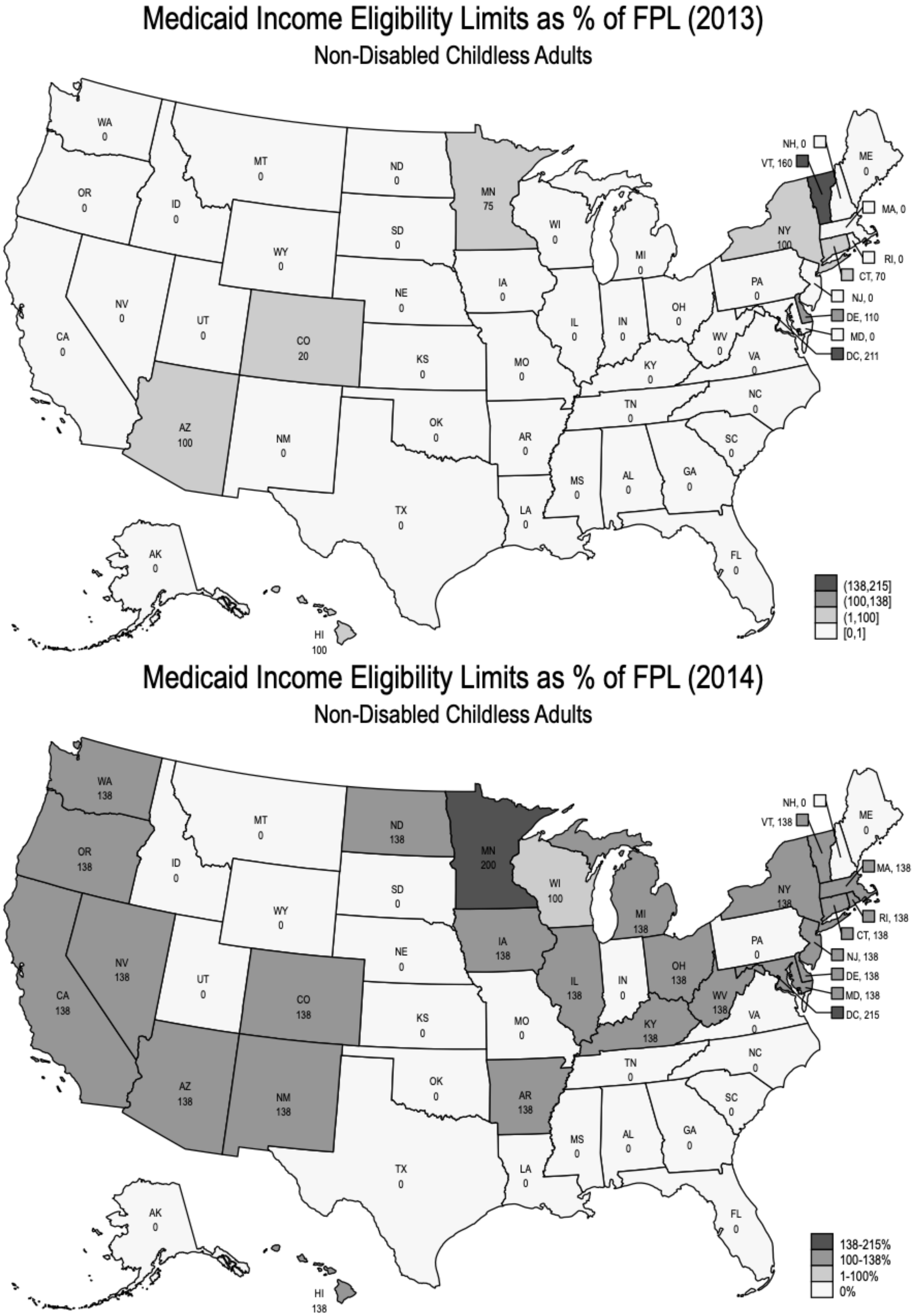
[a] Note that this is not observed as the data used in this analysis is from 2010 to 2017.

Figure A1: ACA Medicaid Expansion Status (2014-2017)



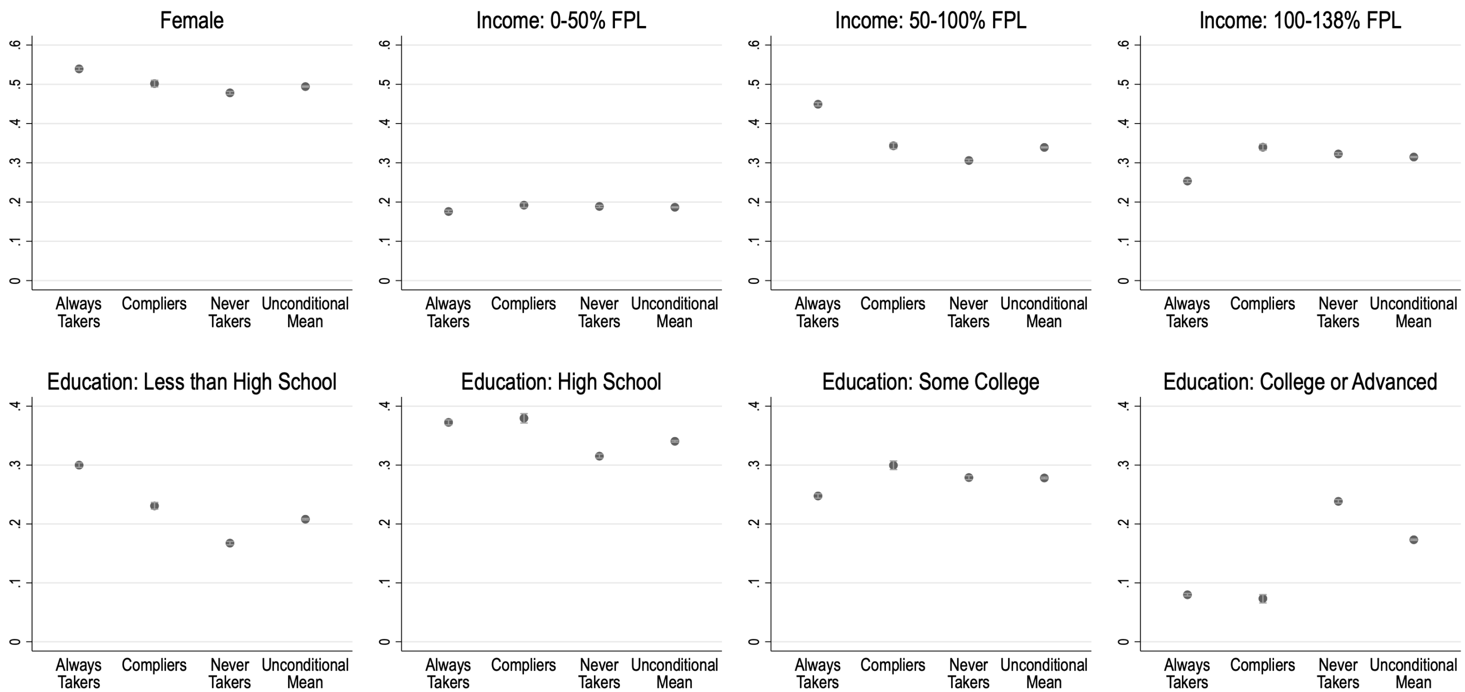
Notes: Figure was created by author using information on states' expansion status from the Kaiser Family Foundation (KFF).

Figure A2: Medicaid Income Eligibility Limits as % of FPL (2013-2014)



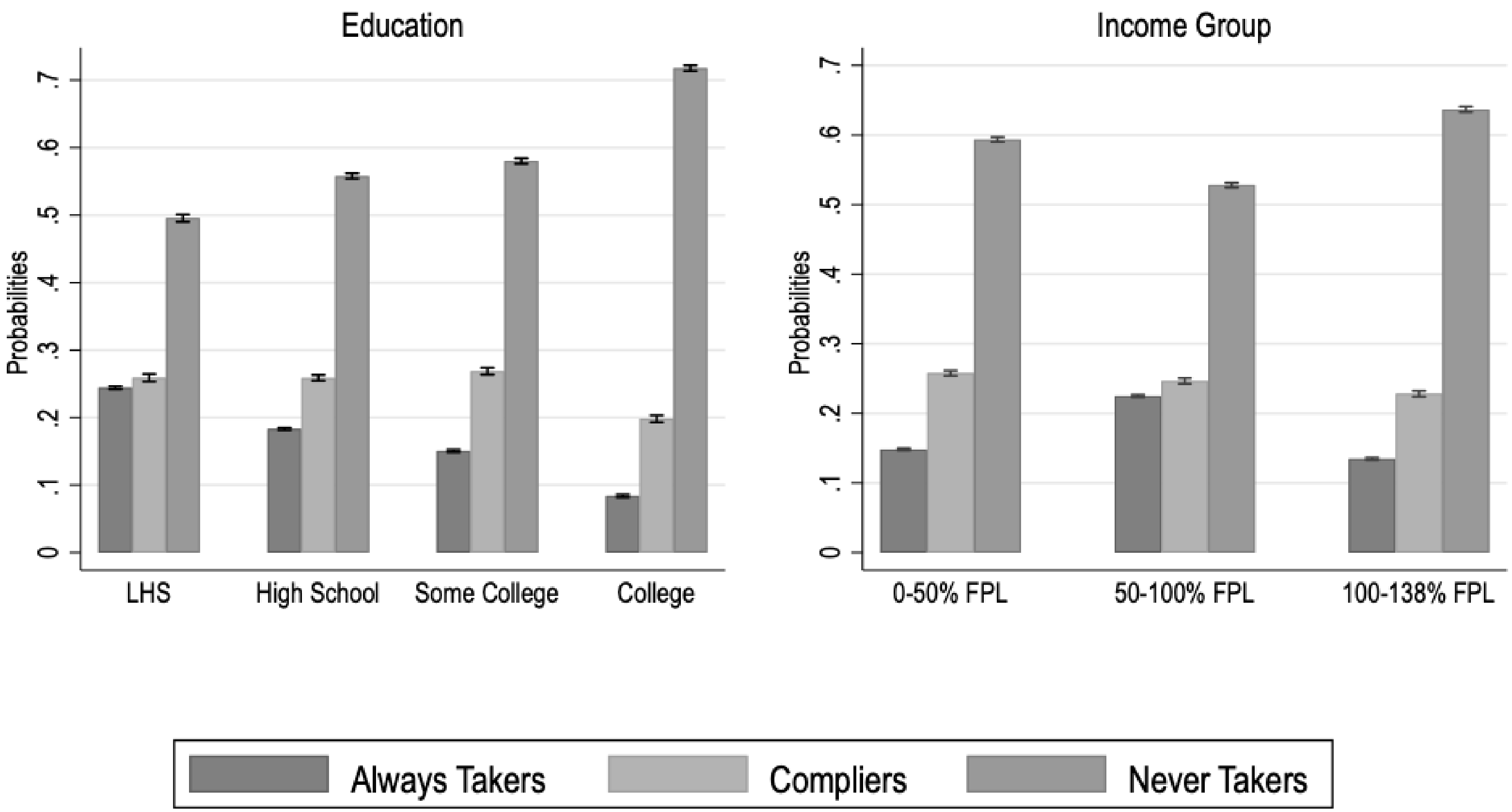
Notes: Figure was created by author using information on states' Medicaid eligibility thresholds rates from the Kaiser Family Foundation (KFF).

Figure A3: Other Observable Characteristics for the Always Takers, Compliers, and Never Takers: Childless Adults (0-138% FPL)



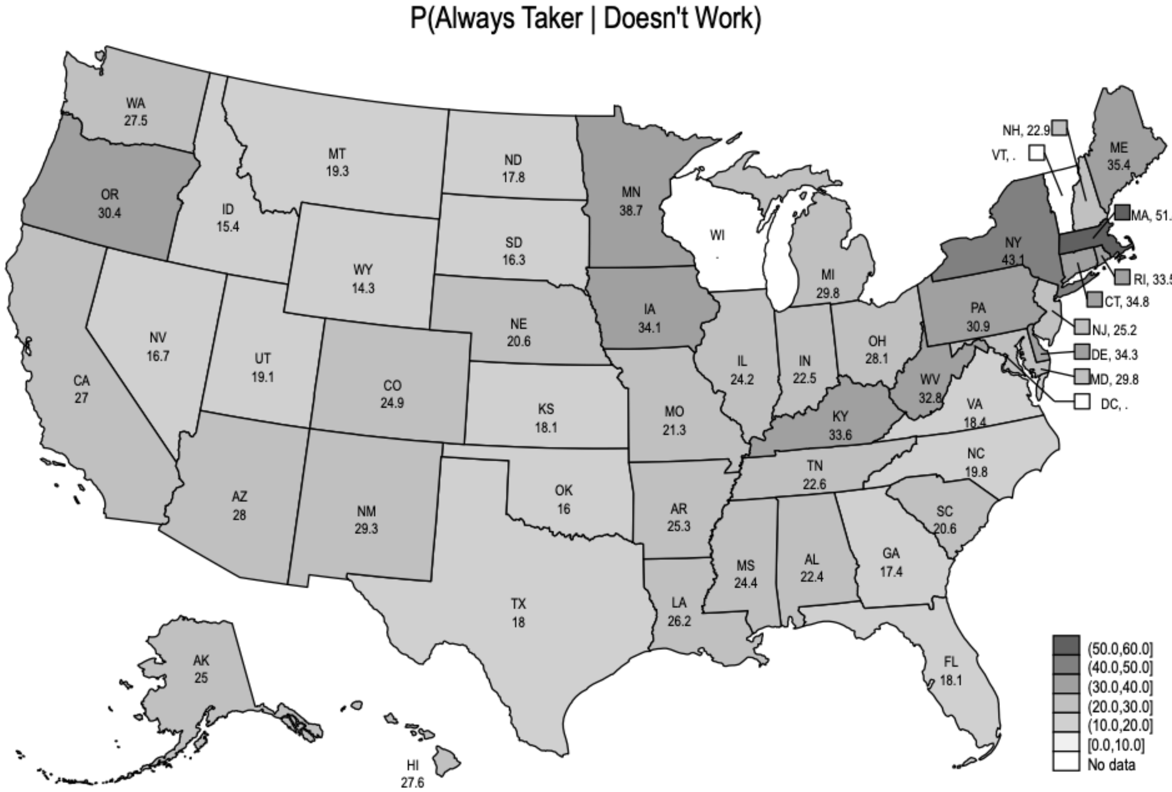
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

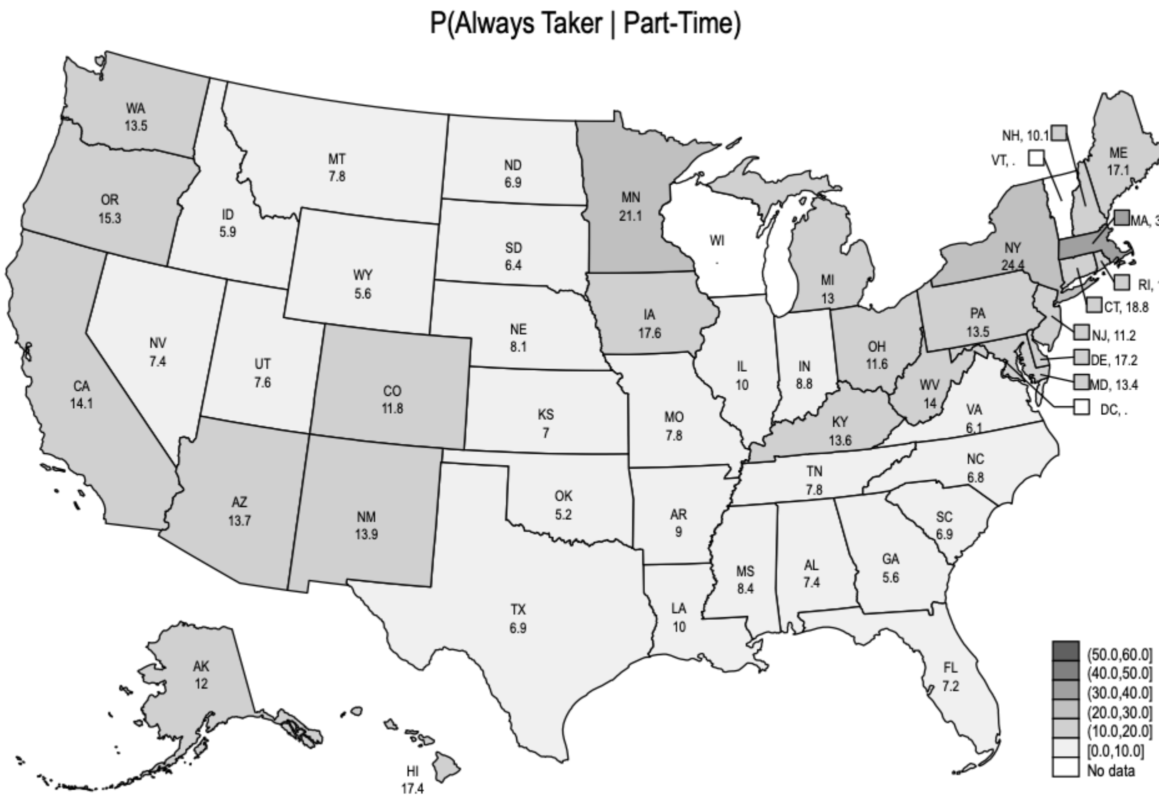
Figure A4: Conditional Probabilities of the Always Takers, Compliers, and Never Takers: Income Group and Education, Childless Adults (0-138% FPL)

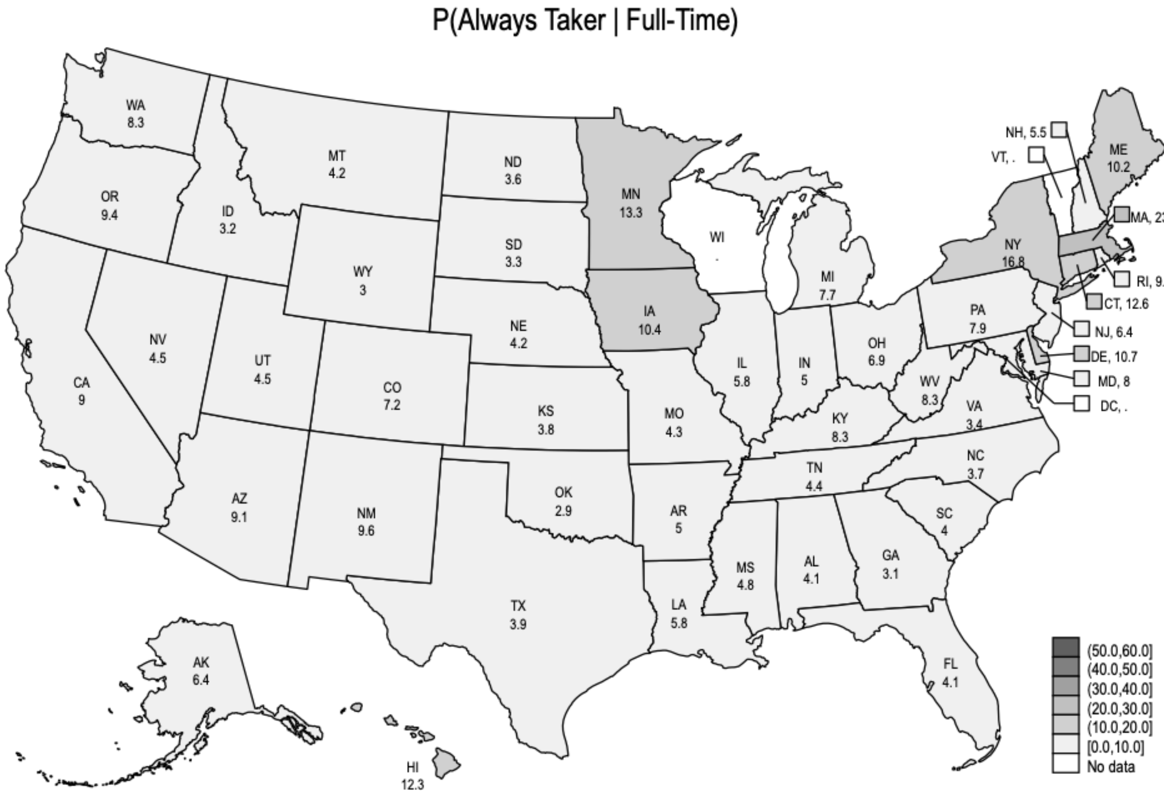


Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A5: State-Level Conditional Probabilities of the Always Takers: Work Status, Childless Adults (0-138% FPL)

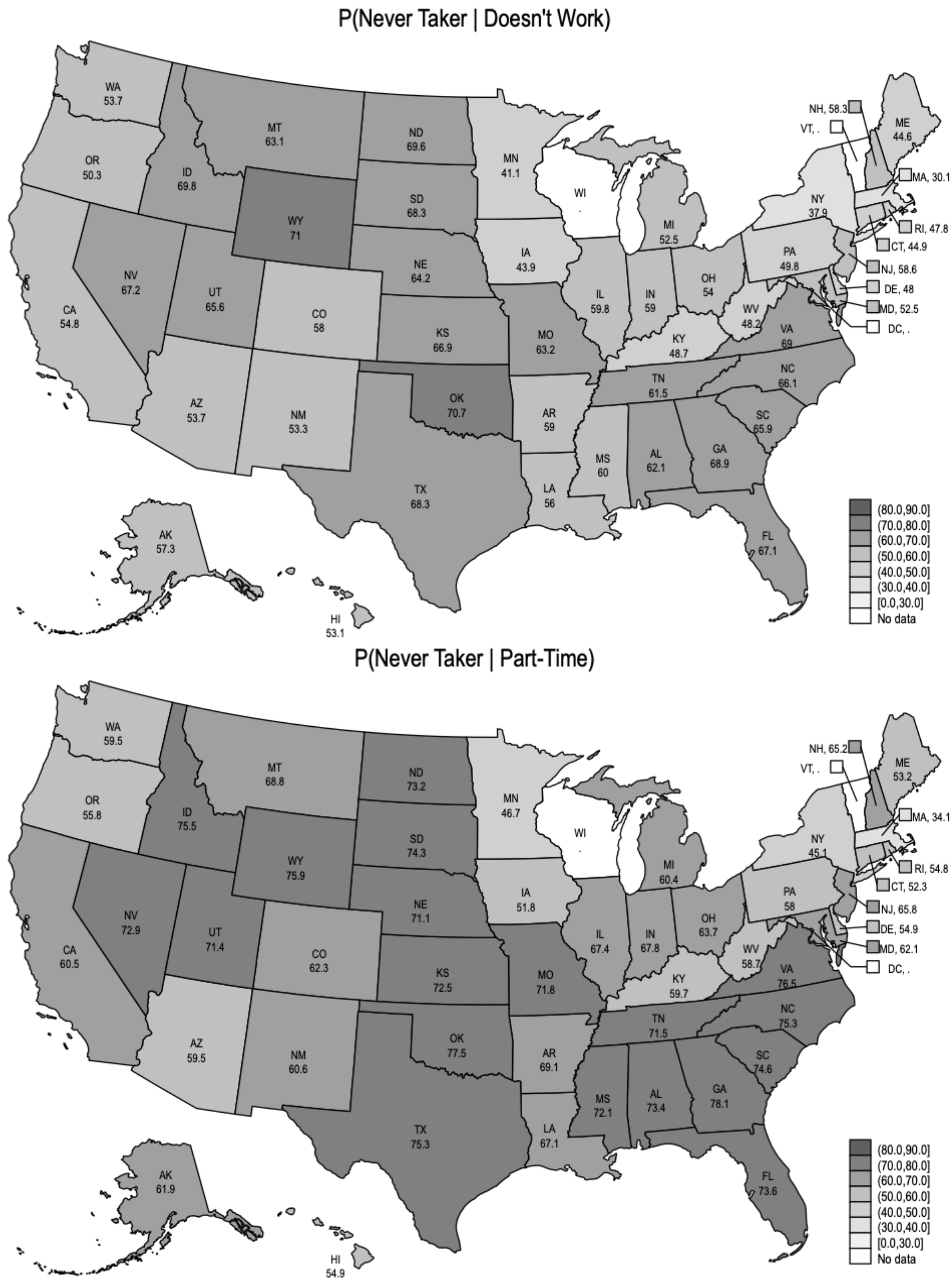


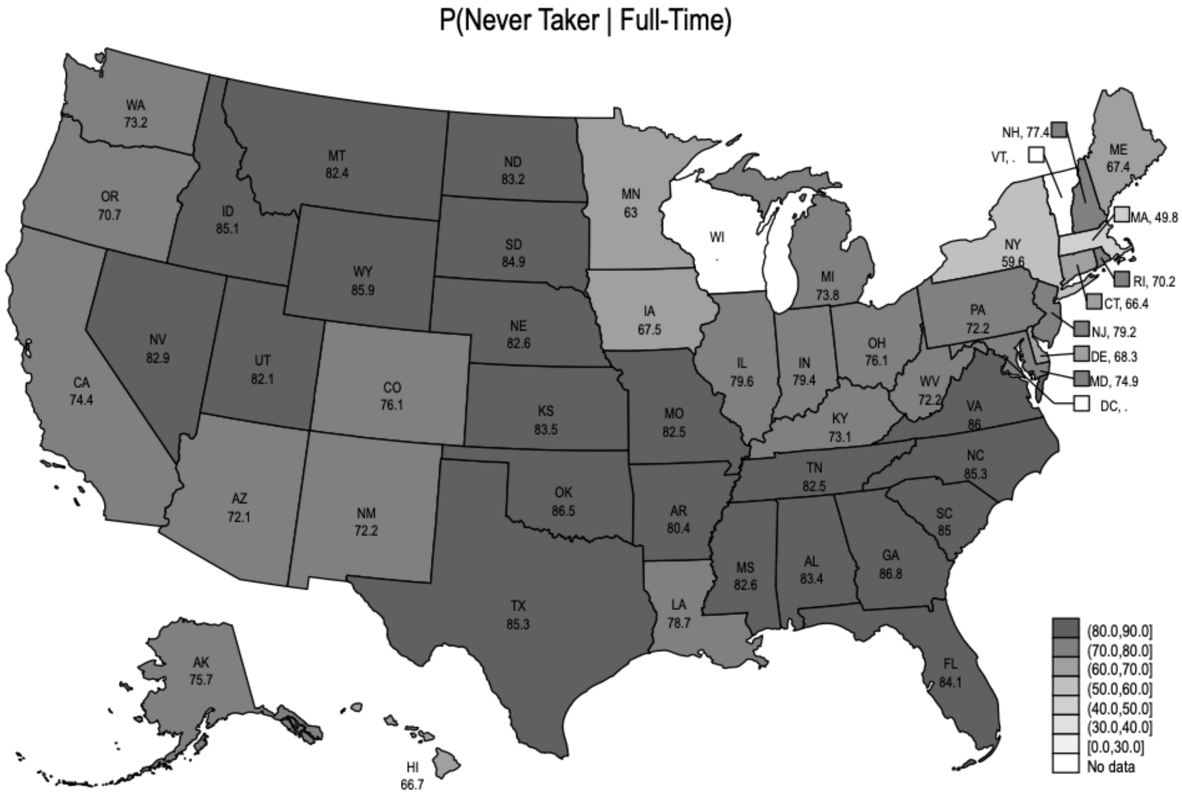




Notes: I report the estimates on the probability of being an always taker for each state using a saturated probit model and methods from Abadie (2003). Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

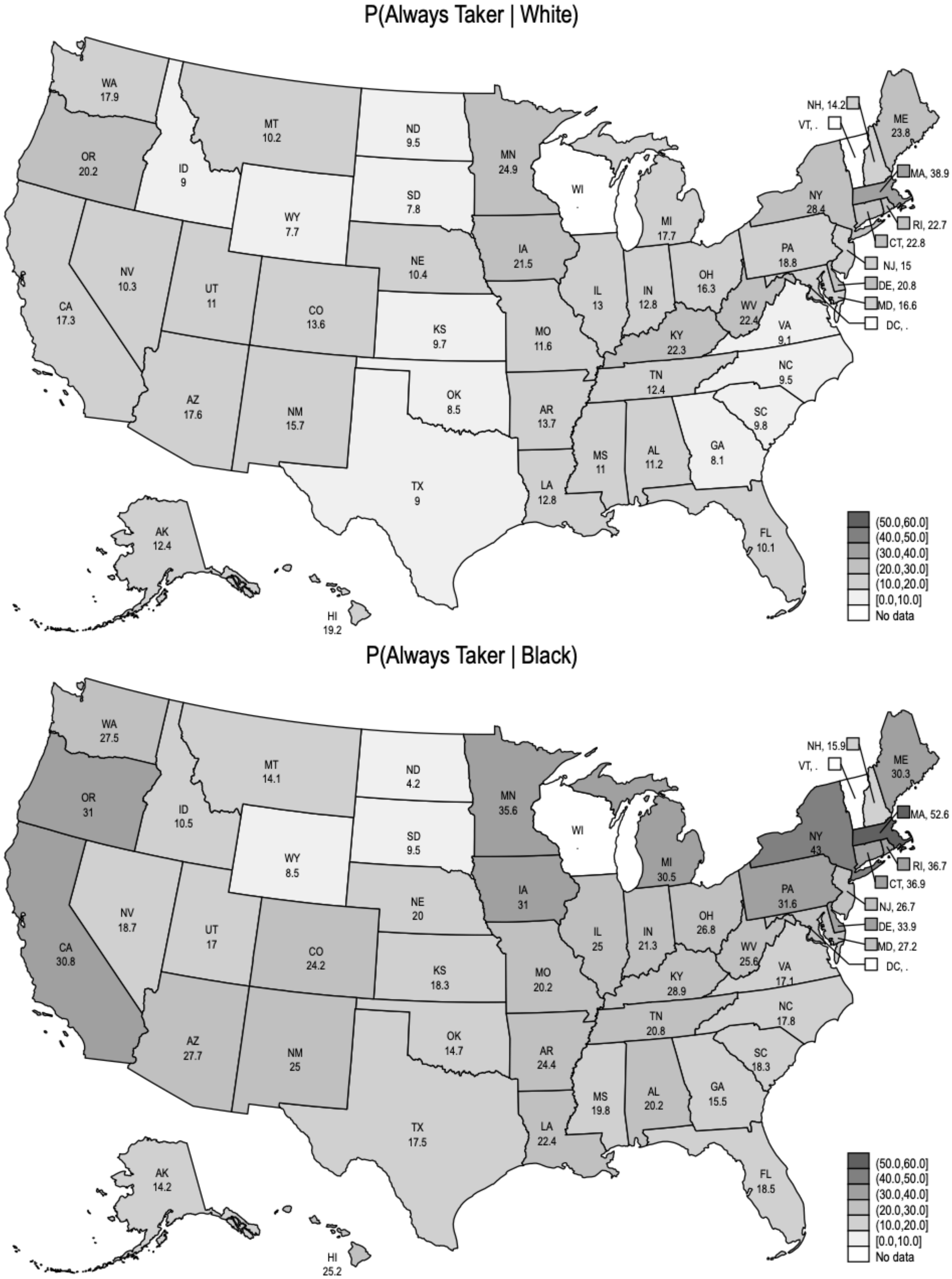
Figure A6: State-Level Conditional Probabilities of the Never Takers: Work Status, Childless Adults (0-138% FPL)

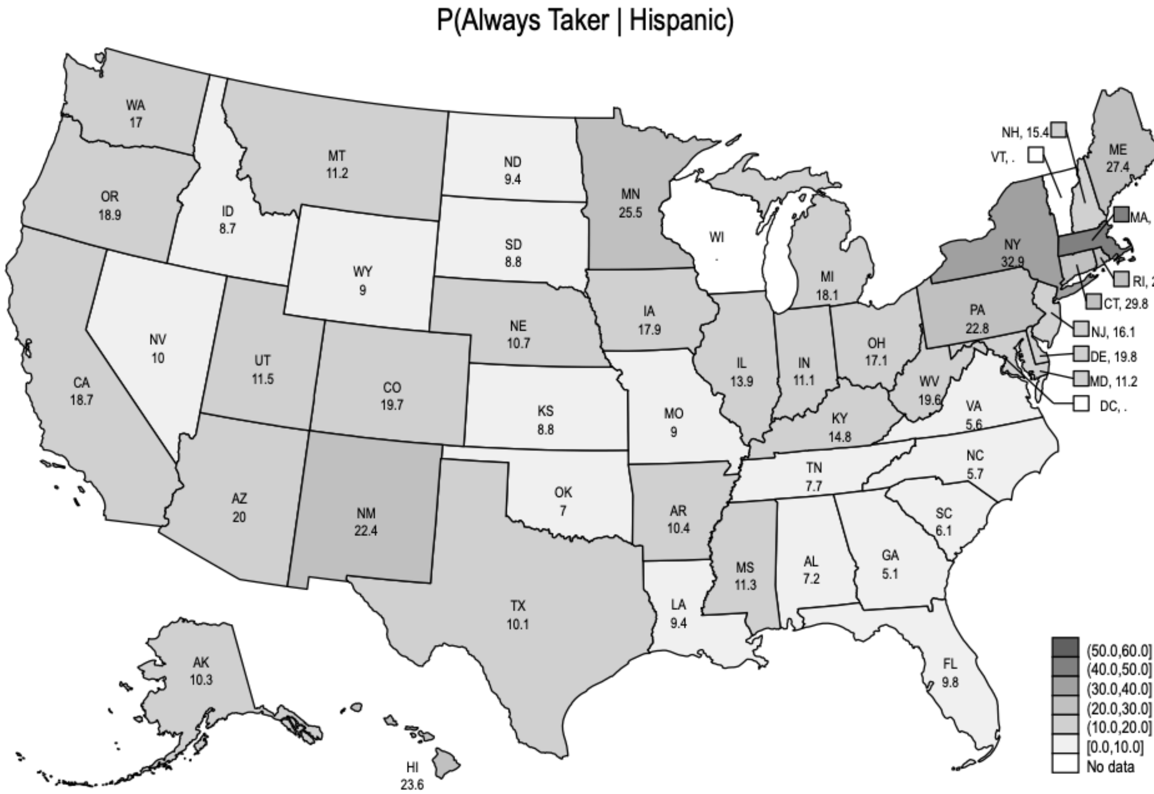




Notes: I report the estimates on the probability of being a never taker for each state using a saturated probit model and methods from Abadie (2003). These include counterfactual estimates for non-expansion states or the probability of being a never taker if that state had expanded Medicaid in 2014.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

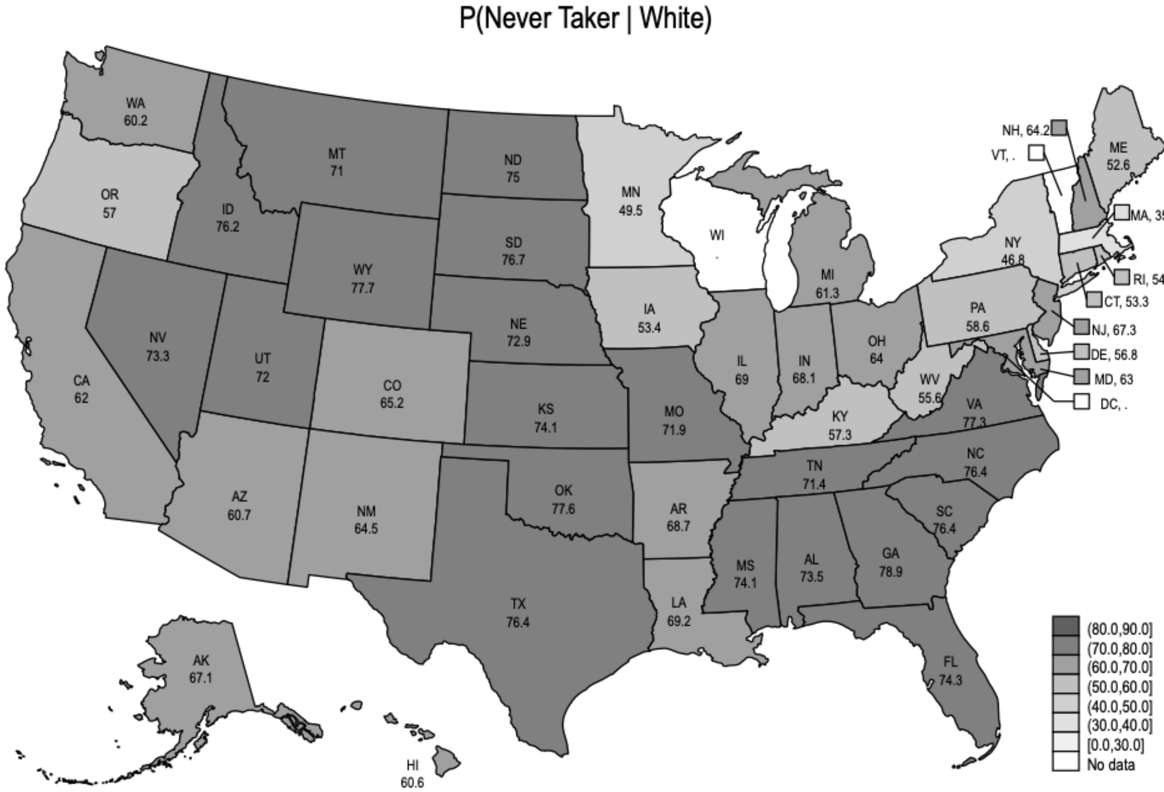
Figure A7: State-Level Conditional Probabilities of the Always Takers: Race/Ethnicity, Childless Adults (0-138% FPL)

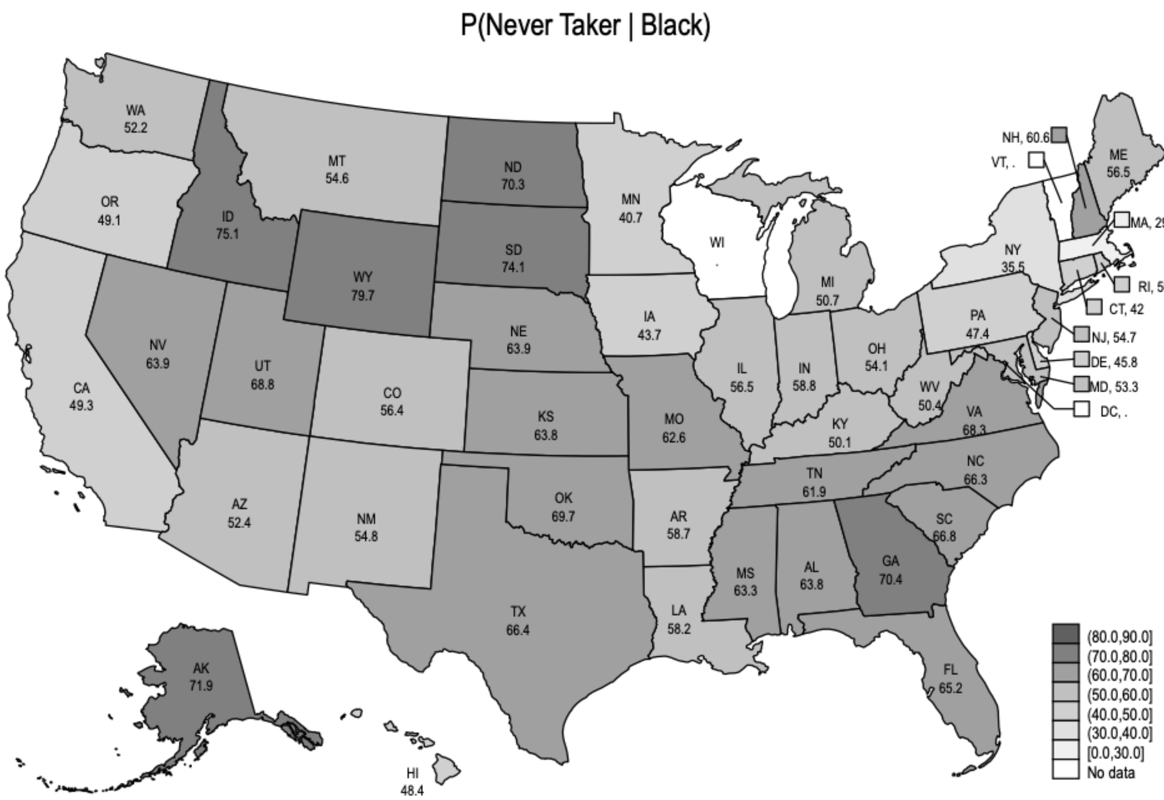


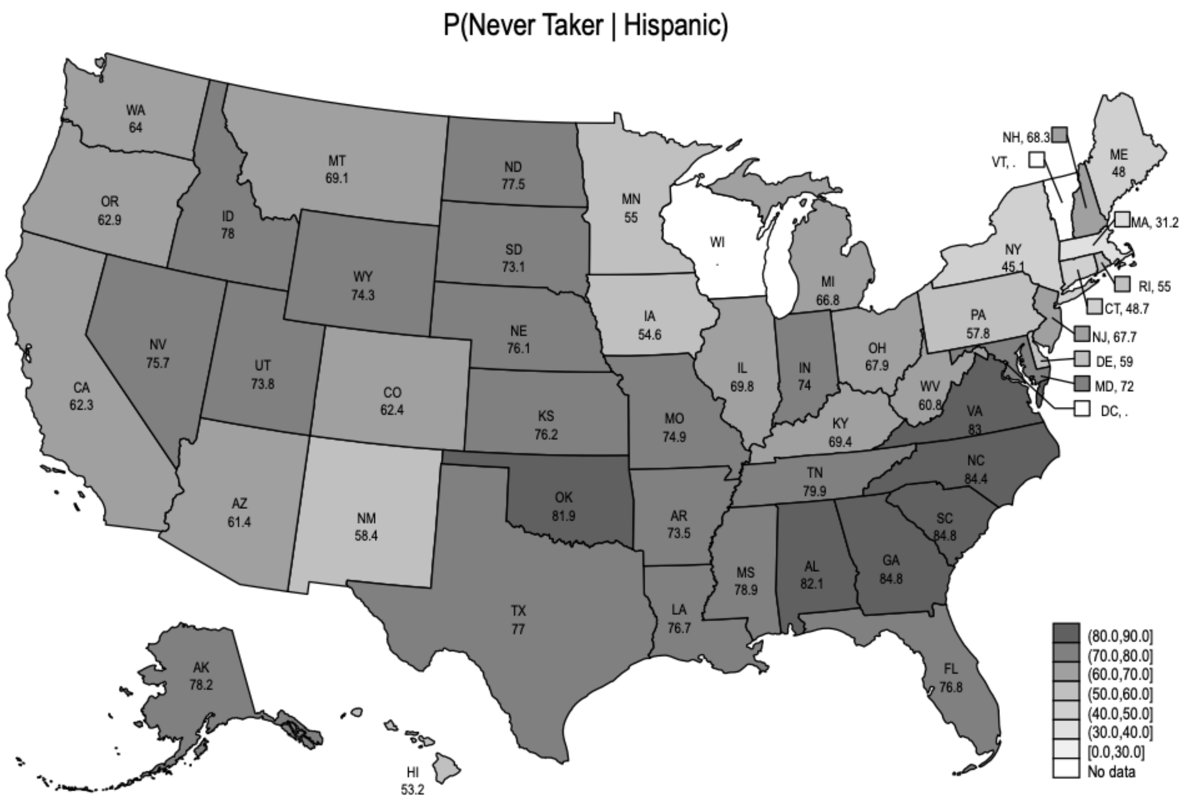


Notes: I report the estimates on the probability of being an always taker for each state using a saturated probit model and methods from Abadie (2003). Estimates for District of Columbia (DC), Vermont (VT), and Wisconsin (WI) are omitted due to the having similar expansions prior to the ACA expansion.

Figure A8: 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.

Appendix B Staggered Treatment Design

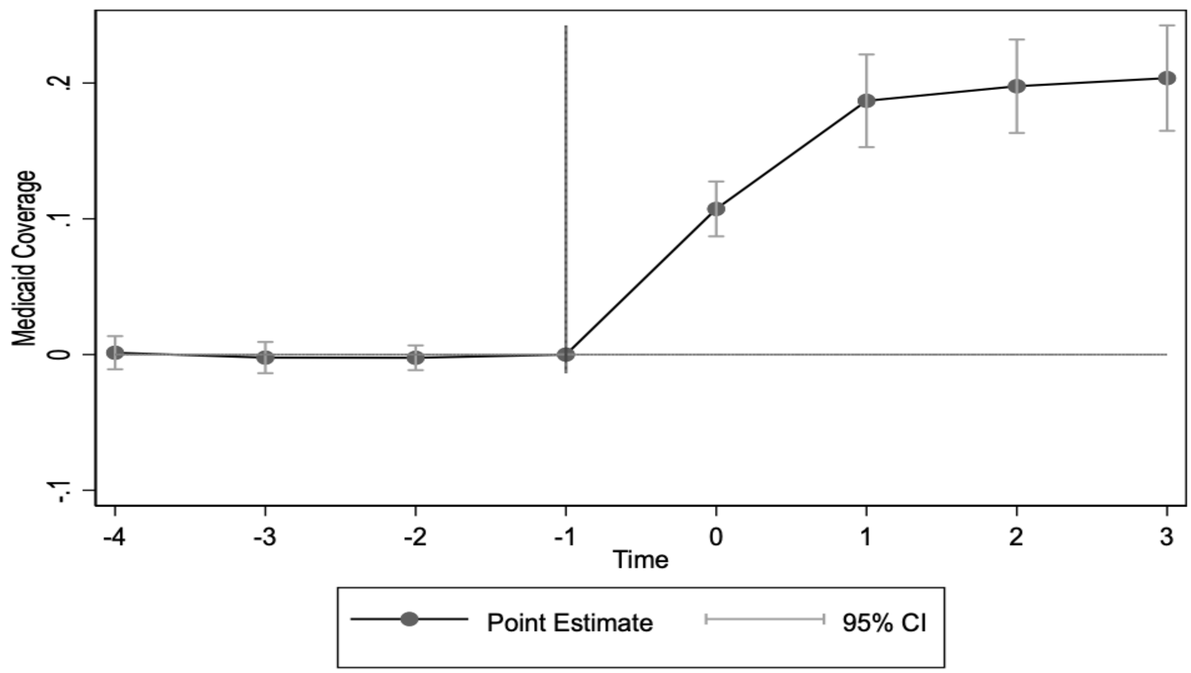
Recently, researchers have been concerned with accurately interpreting the estimates from DID models with variations in treatment timing. In particular, if there are heterogeneous treatment effects across treatment cohorts, then the strict exogeneity assumption is violated. This is caused by the composite 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 B1 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.

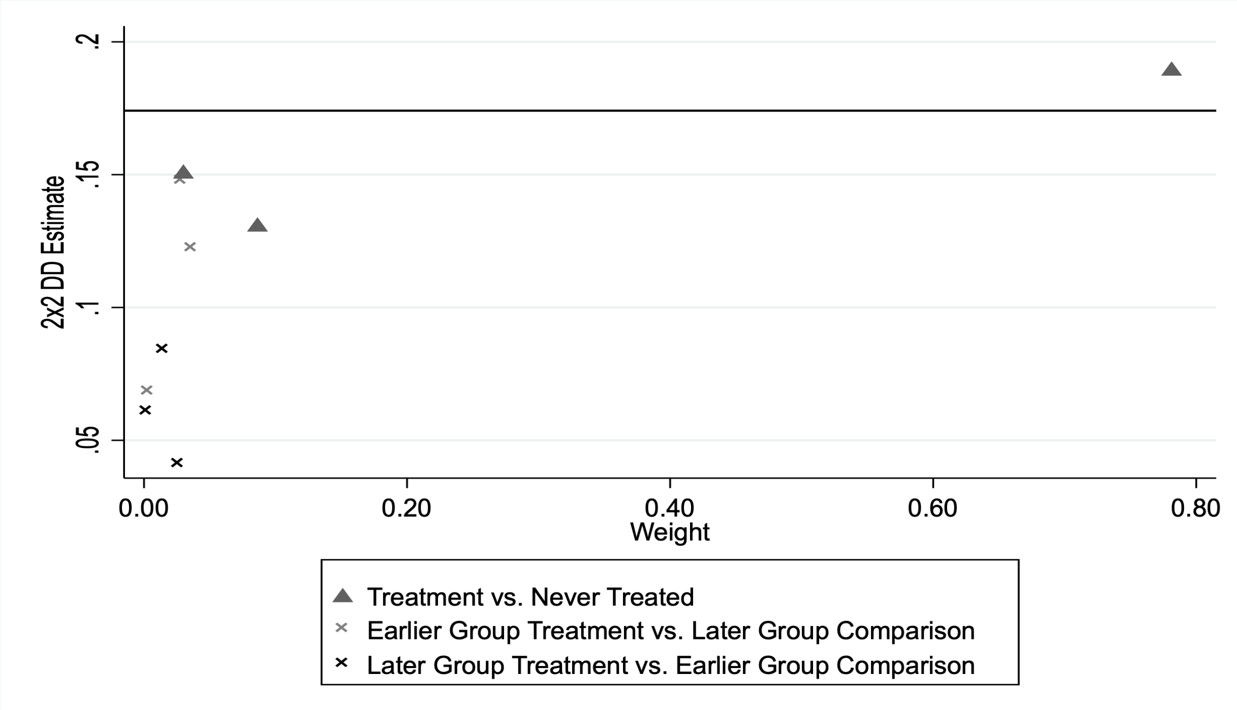
To formally test this, I implement the Goodman-Bacon decomposition that describes the weight and magnitude of the coefficients from each of the 2x2 DD comparisons on the overall two-way fixed effect DD estimate (Goodman-Bacon et al., 2019). Table B1 in the appendix shows that only 4% of the DD estimate 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 B1: 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 B in the appendix for more details.

Figure B2: 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 B for more details.

Table B1: 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