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Who Did the Affordable Care Act Medicaid Expansion Impact? Using Linear Discriminant Analysis to Estimate the Probability of Being a Complier

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Who Did the Affordable Care Act Medicaid Expansion Impact? Using Linear Discriminant Analysis to Estimate the Probability of Being a Complier[†]

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Abstract

What is the likelihood of being a complier in the ACA Medicaid expansion? Using linear discriminant analysis (LDA), I estimate how characteristics relating to socioeconomic status and race/ethnicity affect the likelihood that an individual will be a complier, defined as those induced by the expansion to obtain Medicaid coverage. Across multiple specifications, part-time and full-time workers are more likely than non-workers to be compliers. Not only is this result more prominent for Black individuals, but they are also more likely to be compliers compared to other racial/ethnic groups. This paper not only serves to identify the types of individuals who were directly impacted by the expansion, but it also introduces a new approach that combines complier analysis with techniques from machine learning.

Keywords: Medicaid, ACA, Complier, Linear discriminant analysis

JEL Classifications: I13, I30

1 Introduction

There has been a wide 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. This has motivated researchers to evaluate how the ACA Medicaid expansion disproportionately affected individuals across race/ethnicity and socioeconomic status.[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.

In this paper, I combine techniques in econometrics and machine learning to identify which types of individuals, measured on a set of observables, were most likely to be the compliers under the expansion. First, I adopt methods from previous studies to identify the characteristics of the compliers (Abadie, 2002; Abadie, 2003; Abrigo et al., 2021 ; Imbens and Rubin, 1997; Katz et al., 2001; Kowalski, 2016). Then, using linear discriminant analysis (LDA), I estimate the probability of being a complier using various sets of observables

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

that indicate gender, race/ethnicity, education, work status, income, and other individual characteristics. Additionally, I estimate the probability of being an always taker, those who had already enrolled in Medicaid prior to the expansion, and a never taker, those who had never enrolled even if a state elected to expand Medicaid.

My identification strategy involves several estimation techniques. First, I exploit the design of the 2014 ACA Medicaid expansion and adopt a difference-in-differences (DID) strategy to estimate the impacts of the expansion on Medicaid enrollment for low-income childless adults. Using data from the American Community Survey (ACS) from 2010 to 2017, I find that the expansion increased Medicaid coverage by 15.7 percentage points for low-income childless adults. This result is slightly higher than those reported in previous studies, ranging between 2 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). However, larger impacts have been associated in 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 distributions for work and education. The always takers and never takers are largely from the lower and upper ends of the distributions for work and education, respectively. This finding is similar to what was found in Abrigo et al. (2021) in their evaluation of health insurance expansion for elderly citizens in the Philippines.

Using the estimates discussed above, I employ linear discriminant analysis (LDA) to estimate the probability of being a complier, a never taker, and an always taker, conditional

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

on a set of observables. Moving along the distributions for work and education, I observe negative and positive gradients in the probability of being an always taker and never taker, respectively. This suggests that those at the top and bottom of the distributions for education and work are the least likely to be induced by the expansion to enroll in Medicaid, given their eligibility for preexisting Medicaid programs or for employer sponsored health insurance (ESI), respectively. Across multiple specifications, the probability of being a complier is highest for part-time and full-time workers, and for those in the middle of the education distribution. When evaluating by race/ethnicity, Blacks are the most likely group to be compliers. Additionally, Blacks are mainly part-time and full-time workers from the middle of the educational distribution.

My findings suggest that compared to other racial/ethnic groups, there are underlying factors for low-income Black childless adults that are inducing them to seek Medicaid coverage. This is important given that out of the top 13 states (including DC) that account for 48% of the Black population, only 4 states have elected to expand Medicaid (Buettgens and Kenney, 2016). Therefore, identifying the compliers is valuable for policymakers as it not only identifies the types of individuals that were impacted by the expansion but may also serve to motivate further efforts to address the disparities in health coverage for low-income minorities.

My findings are relevant to the implementation of the Section 1115 Medicaid waivers, which require that users satisfy certain work requirements in order to be eligible for continuous Medicaid coverage.[3] These waivers were created on the premise that Medicaid is a safety net program for the "undeserving poor". While low-income individuals who are either children, pregnant women, elderly, or those with disabilities make up a group largely considered as 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 (Apple-

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

baum, 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 multiple specifications, part-time and full-time workers are more likely than non-workers to be compliers.

Few studies have integrated complier analysis into the context of policy evaluations for health insurance programs (Kowalski, 2016; Ko et al., 2020; Abrigo et al., 2021). None of these studies, however, has attempted to estimate the probability of being a complier. This paper advances the literature by using machine learning techniques to estimate how individual characteristics such as socioeconomic status and race/ethnicity determine the probability of being a complier. To the best of my knowledge, I am the first to combine complier analysis with linear discriminant analysis in any application.

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 probabilities of the compliers, never takers, and always takers derived from LDA. 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]

[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

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]

On January 1st, 2014, twenty five states (including DC) adopted the Medicaid expansion, with seven additional states following between 2014 and 2017. As of January 1st, 2022, 12 states have opted out of participating in the expansion, resulting in Medicaid eligibility for low-income childless adults residing in these states being limited. Figure A1 in the appendix maps each state's expansion status from 2014-2017. 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.[6] 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 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 that equates to 5% of the FPL. Other non-income based features of the ACA improved eligibility determination for Medicaid. This included reductions

eligibility threshold to 138% of the FPL.

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

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

or elimination 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.[7] 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.[8] 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.[9] Figure A2 of the appendix summarizes the changes in the mean Medicaid eligibility thresholds by state between 2013 and 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 ACS surveys approximately 3 million individuals each

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

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

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

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 restrict 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).[10] Poverty status is calculated as a ratio of family income to the poverty threshold set for that individual. For example, the poverty threshold in 2015 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

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

caveat in my study, as respondents may misreport private coverage as public coverage and vice versa.[11]

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 expanded Medicaid to 138% of the FPL in a given year and to the control if otherwise. 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 (KFF). 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.[12]

I restrict my sample to individuals that meet the following criteria: aged between 26 and 64, childless, and non-disabled. 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. Lastly, there are alternative pathways for individuals with disabilities that exist outside of income determination.

I further restrict 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. However,

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

[12] 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.

this sample is subject to measurement error in income for a variety of reasons. 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.

Limiting my sample to those with incomes of less than 138% of the FPL could potentially exclude eligible adults from my analysis. Additionally, states have the option of establishing a “medically needy program” for individuals with serious health conditions whose income exceeds the eligibility threshold rate set by the state. Under the program, individuals may become eligible for Medicaid by “spending down” the amount of income or assets that exceeds a state's medically needy income standard. As a robustness check, I address these concerns by estimating my results separately for those with incomes less than 300% of the FPL. While this addresses the issues summarized above, individuals in this sample may be influenced by the marketplace subsidies available for those whose incomes are between 100% and 400% of the FPL. Nevertheless, performing my analysis with two separate low-income samples allows me to check for potential biases associated with income.

3.2 Summary Statistics

The summary statistics of the individual demographics in the 138% FPL sample by states' expansion status are reported in Table 1. 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 by states' expansion status, non-expansion states had a higher Black population, a lower NHAAPI population, and a greater portion of those who are less educated, working full-time, and with higher incomes.

The summary statistics for the 300% FPL sample are reported in table A1 of the appendix. There are notable differences across income sub-samples. Average income is roughly 67 to 71% FPL for those in the 0-138% FPL group and 164 to 168% FPL in the 0-300% FPL group. The average population of Black childless adults decreased by between 2 to 3 percentage points. This demonstrates a higher concentration of Black childless adults when restricting the sample to those in higher poverty. Next, I observe a drop of 4 to 5 percentage points for those who have less than a high school education. Lastly, the average hours worked increased by roughly 9-10 hours. This is reflected by an increase of 22 to 24 percentage points in full-time status and a decrease of 17 to 19 percentage points in those not working. To summarize, the differences observed between income sub-samples are consistent with explaining the positive relationship between education, employment, and income.

Table 2 shows the time series of the health insurance outcomes for the 138% FPL sample. The mean rate of Medicaid coverage increased before and after the expansion by roughly 20 percentage points in expansion states and by 3 percentage points in non-expansion states. Changes by race/ethnicity in expansion states differ slightly, with increases in Medicaid coverage of 22 percentage points for Whites, 19 percentage points for Blacks, 19 percentage points for Hispanics and 17 percentage points for NHAAPIs. 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 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 likely a result of the availability of private insurance subsidies for those with incomes between 100-400% FPL and residing 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.

I report the time series of health coverage variables for the 300% FPL sample in table A2 of the appendix. Compared to table 2, the average gains in Medicaid coverage have narrowed to roughly 13 percentage points in expansion states and 2 percentage points in non-expansion states, representing a drop in Medicaid eligibility as income increases. Overall, the percentage of those insured by either ESI or non-group private coverage is much higher compared to the 138% FPL sample. However, the changes in private insurance before and after the expansion do not greatly differ across income sub-samples. Lastly, the decreases in the uninsured rate are smaller than what was reported in table 2 at 16 percentage points and 9 percentage points for expansion and non-expansion states, respectively.

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 Angrist et al. (1996) and has recently been applied within the context of health insurance (Kowalski, 2016; Abrigo et al., 2021).[13] I denote treatment status as $D \in \{0, 1\}$ and can be interpreted as enrollment into Medicaid. 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

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

with lower levels of U will accept the treatment relative to those with higher values. Without loss of generality, I normalize U to be a uniform random variable on the unit interval. 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 $D = 1(I \geq 0)$.

4.2 Complier Characteristics

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

Following the methodology from Abadie (2002), I adopt a two-sided non-compliance framework and divide the population into three classes: always takers, never takers, and compliers.[14] Figure 1 summarizes the treatment take-up based on an individual's propensity scores discussed in section 4.1. I layout the methodology in a similar fashion to Kowalski (2016) and Abrigo et al. (2021).

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 ($Z = 0$). In short, if an individual has ($D = 1$) and ($Z = 0$) then they can be identified as an always taker.[15] The always takers could also include individuals that qualified for Medicaid via Supplemental Security Income (SSI) benefits or through state Medicaid programs that

[14]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.

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

existed before the enactment of the 2014 ACA Medicaid expansion.[16] Individuals with $p_0 \leq U < p_1$ are the compliers with $Z = D$. The compliers will enroll in Medicaid $(D = 1)$ only if they reside in states that participated in the expansion at time t $(Z = 1)$. Conversely, they will not enroll in Medicaid $(D = 0)$ if they resided in a state that did not participate in the expansion at time t $(Z = 0)$. The compliers represents 100 x $(p_1 - p_0)$ of the total population, with the measurement scaling the success of the ACA expansion on increasing Medicaid take-up. The never takers are those $p_1 \leq U \leq 1$ and will never enroll in Medicaid $(D = 0)$ even when residing in a state that has participated in the expansion at time t $(Z = 1)$. Therefore, if we observe $(Z = 1)$ and $(D = 0)$ for an individual, then they can be identified as a never taker.

As stated previously, when individuals have $Z \neq D$, they can be separately identified in the data as either an always taker or never taker, depending on the values of Z and D. However, I am unable to distinguish the compliers from either the always takers or never takers at $Z = D$. Individuals with $Z = 1$ and $D = 1$ designate the intervention treated group with the combination of the always takers and treated compliers. Similarly, individuals with $Z = 0$ and $D = 0$ designate the baseline untreated group with the combination of the never takers and untreated compliers. 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 Kowalski (2016) and Abrigo et al. (2021) to solve for the weighted sum of the averages of the characteristics for both the untreated and treated compliers.

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

I estimate the average characteristics of the untreated compliers by solving:

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

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.

Similarly, I estimate the average characteristics for the treated compliers by solving:

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

where ATTC represents the combination of the always takers and the treated compliers.

Then, I compute the average characteristics of the compliers by taking the weighted sum of the solutions to equations (2) and (3).[17]

Following Kowalski (2016) and Abrigo et al. (2021), I run a simple linear regression

[17] I chose the weights that minimizes the variance of the weighted average.

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 ($NTUC$). The coefficients for each of the indicator terms provides the conditional expectations needed to solve for equations (2) and (3). I estimate the following regression:

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

with λ_{NT} being the constant or intercept in the regression. I include year (γ_t) and state (ϕ_s) fixed effects to control for differences across states and time. Using the estimates from the regression, I can now solve for the weighted average of the characteristics of the compliers who could not be separately identified in the data.

4.3 Linear Discriminant Analysis (LDA)

In this section, I introduce the first application of modeling linear discriminant analysis (LDA) with complier analysis. Specifically, I use LDA to estimate the probabilities of the compliers, always takers, and never takers. LDA begins with the assumptions that the observations from each class k are assumed to be multivariate Gaussian and that the classes have equal covariance matrices. In this context, each class corresponds to either an always taker, a complier, or a never taker. I denote x as a column vector of p discriminating variables that corresponds to an observation in the data. I let $P(x \mid G = k)$ denote the probability of observing x conditional on belonging to class k. I model the following multivariate Gaussian distribution:

$$P(x \mid G = k) = \frac{1}{(2\pi)^{p/2} |\sum|^{1/2}} \exp\left[-\frac{1}{2}(x - \mu_k)^T \Sigma^{-1} (x - \mu_k)\right]$$

with μ_k as the mean vector for class k and Σ as the pooled within-class sample covariance matrix. The mean vectors μ_k for each class k are derived from section 4.2.

Next, I denote $P(C \mid x)$ as the posterior probability of being a complier C given observation x. I approximate the LDA posterior probability of observation x being classified as a complier C using equation (5).

$$P(C \mid x) = \frac{P(x \mid C)\,(p_1 - p_0)}{P(x \mid AT)\,p_0 + P(x \mid C)\,(p_1 - p_0) + P(x \mid NT)\,(1 - p_1)} \tag{5}$$

The terms $P(x \mid AT)$, $P(x \mid NT)$, and $P(x \mid C)$ designate the class-conditional densities of x for the always takers, never takers and compliers, respectively. The propensity scores are calculated using methods that I will discuss in section 4.4. I modify equation (5) to estimate the posterior probabilities for the always takers and never takers by replacing numerator with their class-conditional densities $P(AT \mid x)$ and $P(NT \mid x)$ multiplied by their respective propensity scores. Lastly, I conduct inference and report the means and 95% confidence intervals for the posterior probabilities from 1000 bootstrapped re-samples.

4.4 Difference-in-Differences

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 $p_1 - p_0$, which corresponds to the effects of the ACA Medicaid expansion on Medicaid coverage. The propensity scores are used in equation (5) to estimate the posterior probabilities of the compliers, always takers, and never takers. I run the following regression:

$$D_{ist} = \beta_0 + \beta_1 Z_{st} + \beta_2 X_{ist} + \gamma_t + \phi_s + \epsilon_{ist} \tag{6}$$

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.[18]

Theoretically, all individuals whose incomes are less than 138% should be eligible for Medicaid if they reside in a state that adopted the Medicaid expansion at time t. 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 represents the potential increase in Medicaid enrollment for those who became eligible under the Medicaid state expansion. The term X_{iast} represents a set of observables X_{iast} 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. I cluster all standard errors at the state-level to account for possible serial correlation (Bertrand et al., 2004). Note that I do not include separate terms for the post treatment year and states' expansion status as they are subsumed by the year and state fixed effects.

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

The key assumption of a DID design is the parallel trends assumption, stating 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 adopt an event study framework similar to Miller et al. (2021) that assesses the changes in health insurance outcomes while controlling for fixed differences across states and national trends over time. The specification for the event study is as follows:

$$D_{ist} = Z_{st} \times \sum_{\substack{y=-4 \\ y\neq-1}}^{3} \beta_y I(t - t_s^* = y) + \beta_x X_{ist} + \gamma_t + \phi_s + \epsilon_{ist} \tag{7}$$

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 do this to avoid multicollinearity in the relative time indicators. I "trimmed" the data by omitting values for $y < -4$ since I observe $y < -4$ only for late expansion states.[19] 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 (7) using a linear probability model with ACS survey weights and cluster the standard errors at the state level.[20]

[19]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.

[20]Recently, researchers have expressed 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. In response, I perform several robustness checks in section B of the appendix using techniques from previous studies to evaluate whether staggered treatment is a concern in my design (Goodman-Bacon 2021 and Sun and Abraham 2021).

I summarize the methodology of estimating the posterior probability of the compliers, always takers, and never takers in five steps. First, I run the regression in equation (6) to predict the propensity scores p_1 and p_0. Second, I estimate the class conditional expectations of the always takers and never takers 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. Fourth, I calculate the class conditional density functions for each set of individual characteristics using the class conditional expectations for the compliers, always takers, and never takers. Finally, I utilize the density functions, propensity scores, and conditional expectations to estimate the posterior probabilities of the compliers, always takers and never takers for each set of observables in equation (5).

5 Results

5.1 Estimating the Probability of Medicaid Take-up

In Table 3, I provide the results from the DID regression in equation (6) 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 Medicaid coverage, ESI, non-group private insurance, or being uninsured, respectively. Columns (4) - (8) provide the results for childless adults with incomes below 300% of the FPL. 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, ranging between 10.2 to 15.7 percentage points, depending on the income subgroup. 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 longer time periods, this results in the size of my estimates being slightly higher than what is reported in the literature.

I observe some evidence of crowd-out in private health coverage. The Medicaid expansion reduced ESI by approximately 1.2 to 1.7 percentage points, depending on the income subgroup. Reductions in non-group private insurance are approximately 2.8 to 4.6 percentage points. The coefficients for private insurance and the uninsured rate sum nearly to the amount reported for Medicaid in both subgroups, showing limited evidence that beneficiaries are dual enrolling into Medicaid and private insurance.[21] My results suggest that among low-income childless adults, approximately 40% of gains in Medicaid can be explained by crowd-out of private coverage and 60% represents 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 between 23% to 33% (Courtemanche et al., 2017; Kaestner et al., 2017). However, it is important to note that both studies did not restrict their sample to low-income childless adults, utilized different empirical strategies and were more restrictive on which states were considered treated (i.e., states were consider treated only if they expanded with no prior history).

The parallel trends assumption 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 (7) to test this assumption. In addition, the event-study model allows the observation of dynamic treatment

[21] I test to see if the linear combination of the coefficients sum to zero. While I unable to reject the null in the 138% FPL sample, I can reject the null at the 10% level in the 300% FPL sample.

effects across time. The results of the event-study are presented in Table A3 of the appendix. Figures 2 and A3 illustrate the results of the sample groups below 138% of the FPL and below 300% of the FPL, respectively. 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.

The patterns of the event studies are similar across both low-income sub-samples. In the pre-period, I observe near zero and insignificant effects of the ACA expansion on all health insurance variables for both low-income sub-samples. Therefore, my estimates are consistent with the parallel trends assumption. In the post-period, I observe positive and statistically significant changes in Medicaid coverage over time. These increases potentially reflect heightened awareness, individual mandate, reductions in enrollment barriers, and improvements in outreach strategies brought upon by the ACA and directed for low-income childless adults. Consistent with the main results of the DID regression outlined in equation (6), I observe negative and statistically significant changes in private coverage and uninsured rates for both low-income sub-samples.

5.2 Complier Characteristics Results

I compute the average characteristics of the compliers and compare them to those of the never takers and always takers using the parameters derived in equation (4). Figures 3 and 4 report the results for the 0-138% FPL group. The results for the 0-300% FPL group are reported in Figures A4 and A5 of the appendix.[22] Each graph plots a separate individual observable with the means and 95% confidence intervals calculated from 1000 bootstrapped re-samples. I report my estimates individually for the always takers, compliers, never takers, and unconditional mean. Due to the large sample size of the ACS, the estimates do not

[22]Tabulated versions of these figures are reported in tables A4 and A5 of the appendix.

exhibit much noise, resulting in the small size of the confidence intervals.

Females are only slightly more likely to be compliers than males. However, in both income sub-samples, the compliers are disproportionately from the middle of the education distribution and work distribution. This finding is similar to that found in Abrigo et al. (2021). The complier means for part-time workers are above those of the never takers and always takers. Those not working are disproportionately always takers, while those working full-time are disproportionately never takers. The complier means for those with at most a high school degree are above the means of the always takers and never takers. The complier means for those who have completed some college are either above or slightly below the means of the always takers and never takers, depending on the income sub-sample. Those with less than a high school degree are disproportionately always takers, while those with a college/advanced degree are disproportionately never takers.

The composition of the compliers varies between Whites and Blacks, depending on the income sub-sample. In the 138% FPL sample, the complier means for Whites are above the means of the never takers and always takers, but then fall below the means in the 300% FPL sample. The exact opposite occurs for Blacks in both income sub-samples. Both Hispanics and NHAAPIs are less likely to be compliers. The complier means for Hispanics are below the means of the never takers and always takers in both sub-samples. Lastly, the complier means for NHAAPIs exhibited patterns similar to those of Hispanics but to a greater degree.

Additionally, I find that the compliers are from the middle of the age distribution, with young adults and older adults making up the never takers and always takers, respectively. Observing by income, the compliers are more likely to be those with incomes between 100-138% FPL. In the 0-300% FPL sample, I observe that the lower and higher ends of the income distribution consist mainly of always takers and never takers, respectively. Lastly, the compliers are less likely to have private insurance or be non-U.S. citizens. This is evident as the complier means for both non-U.S. citizens and holders of private insurance are below those of the always takers and never takers.

There are a few takeaways from performing a complier analysis in the setting of the ACA Medicaid expansion. First, the compliers are mainly those from the middle of education distribution and work distribution. Those uneducated or 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 highly educated or working full-time likely received ESI coverage through work, therefore, they opted to not 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 distributions for work status and education already qualified for insurance, explaining why those in the middle are more likely to be compliers.

Second, when transitioning from the 138% FPL sample to the 300% FPL sample, the compliers means for Blacks increased as opposed to other racial/ethnic groups where the opposite occurs. This demonstrates that even at higher incomes, Black individuals are more likely than other racial/ethnic groups to be compliers. Additionally, I find that NHAAPIs are the least likely to be compliers compared to all other racial/ethnic groups. Past research has suggested that NHAAPIs hold negative views towards public coverage and also face difficulties with Medicaid enrollment processes (Sommers et al., 2012; Allen et al., 2014; Park et al., 2019).

5.3 LDA Results

In this section, I employ linear discriminant analysis (LDA) to estimate the posterior probabilities of the compliers, always takers, and never takers across various sets of observables. First, I focus on variables relating to gender, race/ethnicity and socioeconomic status. For simplicity, I restrict my estimations to only three discriminating variables. Each panel corresponds to a different class and set of discriminating variables, containing the mean posterior probabilities and 95% confidence intervals computed from 1000 bootstrapped re-samples.

I evaluate the posterior probabilities of each class across gender, race/ethnicity, and education in figure 5. I do not observe any notable differences by gender, although females are slightly more likely to be always takers and slightly less likely to be never takers. However, I find that the probability of being a complier is slightly higher for those in the middle of the distribution for education and is consistent across all racial/ethnic groups except for NHAAPIs. As education increases, I observe positive and negative gradients in the probabilities of the always takers and never takers, respectively.

Blacks have the highest likelihood of being a complier compared to other racial/ethnic groups. Additionally, they are more likely to be always takers and less likely to be never takers. Hispanics are less likely to be compliers compared to Whites despite both having nearly identical rates for the always takers. This is due to the probability of being a never taker being higher for Hispanics compared to Whites. Similarly, despite NHAAPIs having only slightly smaller rates for the always takers compared to Whites, the rates of the never takers are the highest amongst all racial/ethnic groups. This results in NHAAPIs having the lowest rates of the compliers. This supports previous studies that cited barriers relating to accessibility, financial burden, and perceived need being prevalent among racial/ethnic minorities, primarily for Hispanics and NHAAPIs (Weech-Maldonado et al., 2003; Andersen et al., 2007; Park et al., 2019; Michener, 2020). In table A6 of the appendix, the probability of being a complier increases for Blacks, but decreases for all other racial/ethnic groups in the 300% FPL sample. This suggests that at higher incomes, more Black childless adults are qualifying for Medicaid and choosing to enroll. The converse holds true for other racial/ethnic groups, which suggests that they are selecting private coverage over Medicaid.

Next, I present my results for gender, race/ethnicity and work status in figure 6. The patterns for race/ethnicity and gender do not greatly differ from those presented in figure 5. However, consistent across race/ethnicity and gender, part-time and full-time workers are much more likely to be compliers compared to non-workers. Moving along the work distribution, I observe positive and negative gradients in the probabilities of the never takers and always takers, respectively. When moving to the 0-300% FPL sample in figure A7, the complier means for part-time workers greatly exceed those of the other work groups. This demonstrates that even at higher incomes, the Medicaid expansion primarily induced enrollment for those who worked at least part-time over those who didn't work at all. Therefore, the characteristics of the compliers do not align with those that define the "undeserving poor".

Seeing from section 5.2 that the compliers are disproportionately those from the middle of the education and work distributions, I run LDA across work status, education and race/ethnicity and report my findings in figure 7. I select race/ethnicity over gender as the former exhibited wider heterogeneity in previous figures. The patterns in work status are similar to those presented in table 6. Moving up the categories for education and work status, I observe negative and positive gradients in the probabilities of the always takers and never takers, respectively. However, there is little variation in the probabilities of the compliers across education, aside from seeing lower rates for those with a college/advanced degree. This is consistent across all racial/ethnic groups except for Blacks who are concentrated in the middle of the education distribution. This demonstrates that, on average, work status is a stronger predictor than education in explaining the differences in the probability of being a complier.

In figure 8, I estimate the probability of being a complier across various indicators of socioeconomic status, specifically education, work status, and income. Consistent across work and education, those with incomes between 100-138% FPL are more likely to be compliers compared to other income groups. This is likely a result of having incomes that were too high to qualify for programs that existed prior to the expansion, but just below the maximum threshold set under the expansion. Interestingly, those at the bottom of the income distribution at 0–50% FPL are less likely to be always takers compared to those with incomes between 50-100% FPL. This could imply that those in extreme poverty were either unaware that they were eligible, or faced barriers that prevented them from enrolling.[23]

Andersen et al. (2007) argued that age serves as a predisposing contextual characteristic that affects the need and demand for health insurance. Therefore, I report my results across gender, age group, and race/ethnicity for both income sub-samples in figures A10 and A11 of the appendix. The results imply that, consistent across race/ethnicity and gender, there is a positive relationship between demand for health insurance and age among low-income childless adults. This is evident as older adults (aged 55-64) are more likely to be always takers, while younger adults (aged 25-34) are more likely to be never takers. Those in the middle age group (aged 35-54) are the most likely age group to be compliers and, by extension, the most likely group to be induced by expansion to enroll in Medicaid. Older adults were likely to have exhausted all options to enroll in Medicaid prior to the expansion, whereas younger adults were unlikely to seek coverage all together. Therefore, the Medicaid expansion was effective in expanding the age range in which low-income childless adults enrolled.

Much of the stigma surrounding the "undeserving poor" has been centered on perceptions of deservingness concerning undocumented immigrants. Therefore, I perform LDA across gender, race/ethnicity and citizenship status for both income sub-samples in figures A12 and A13 of the appendix. Non-U.S citizens are much less likely to be compliers compared to U.S. citizens. This finding supports previous work that has discussed how

[23]Previous studies have cited a phenomenon known as the "welcome mat" or "woodwork" effect where recipients who were unaware that they were eligible for Medicaid prior to expansion enrolled only after the expansion took place (Frean et al., 2017; Hudson and Moriya, 2017). While this effect has been studied for parents and children, not much is known about how this affected childless adults who were eligible for programs that offered limited Medicaid assistance prior to the ACA.

immigrants faced enrollment barriers relating to fear, confusion, and language and literacy challenges (Stuber et al., 2000; Kaiser Family Foundation, 2021). Non-U.S citizens are ineligible for Medicaid unless they meet the requirement of waiting at least five years to receive "qualified" immigration status before becoming eligible. This creates an additional barrier that "non-qualified" immigrants face, as eligibility extensions under the ACA expansion do not apply to them.[24] The results by race/ethnicity are consistent with the results from previous figures, although non-U.S Hispanic citizens are slightly more likely to be compliers than non-US White citizens. Overall, my findings do not support the belief that Medicaid favors non-U.S citizens over U.S citizens. In fact, this provides evidence that the sentiments and antipathy towards undocumented immigrants have negative consequences for Medicaid enrollment for these individuals.

Lastly, I evaluate how the posterior probability of the treatment groups changes when I condition for private insurance. I present my results across gender, race/ethnicity, and private insurance types for both income sub-samples in figures A14 and A15 of the appendix. The probabilities of the compliers for both insurance types are low, with ESI being slightly higher in both figures. I advise caution in interpreting these results as I cannot determine whether this is a product of crowd-out of private coverage or dual enrollment patterns of both Medicaid and private insurance. However, the results from table 6 suggest that there are moderate levels of crowd-out and limited evidence of dual enrollment across both income sub-samples. This leaves me to believe that my results are motivated by the crowd-out of private insurance, although additional research is needed to substantiate this claim.

[24] Exemptions exist for some groups (refugees, asylees, and lawfully permanent residents who were formally refugees, or asylees).

6 Policy Implications and Conclusion

This paper introduces techniques that estimates the probability of being a complier within the setting of the ACA Medicaid expansion. This study is the first to combine LDA with complier analysis in any application observed in the literature. Using national data from the ACS, I employed LDA to identify which characteristics for low-income childless adults are salient in predicting the probability of the compliers from the ACA expansion.

The compliers are more likely to be part-time and full-time workers in the middle of the education distribution, which is consistent across all racial/ethnic groups. This finding is particularly strong for Black individuals. Across various sets of observables, Black individuals are more likely on average to be either compliers or always takers compared to other racial/ethnic groups. Additionally, I find that the probability of being a never taker is much higher for Hispanic and NHAAPI individuals compared to White individuals. This potentially suggests barriers to accessibility that are intrinsic to race/ethnicity and have not been completely addressed under the ACA Medicaid expansion.

The findings from this paper have very important policy implications concerning Medicaid. States are currently engaging in efforts to waive restrictions against imposing work requirements under Section 1115 waivers as a determination for Medicaid eligibility. The implementation of these requirements is motivated by the belief that Medicaid recipients are unmotivated to work, despite the fact that approximately 60% of non-elderly and non-disabled adults on Medicaid already work part-time or full-time (Garfield et al., 2017). 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 uninsured (Sommers et al., 2019). My findings challenge the motivation behind the implementation work requirements under Section 1115 waivers, seeing that the compliers in the ACA Medicaid expansion cannot be identified with the characteristics that define the "undeserving poor".

This paper has only "scratched" the surface by focusing on health coverage rather than health services. However, given that health insurance has been linked to better access and receipt of care, reductions in mortality, and improvements in health status and financial security (Sommers et al., 2017), expanding Medicaid in states that have yet to do so will not only provide health insurance to many low-income childless adults trapped in the coverage gap, but will also assist in addressing the health disparities that are prevalent for low-income individuals. This is especially crucial for Black childless adults as they heavily reside in non-expansion states but are also the most likely racial/ethnic group to be compliers. It is with hope that the techniques in this paper will motivate future work in identifying the compliers and encourage new approaches in assessing whether the health care needs of the compliers are being met.

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Table 1: Summary Statistics of Control Variables by States' Expansion Status (0-138% FPL)

	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)
AANHPI	0.09	(0.28)	0.09	(0.29)	0.03	(0.17)	0.04	(0.18)
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

	AANHPI Low-Income Individuals					
	Expansion States			Non-Expansion States		
	Before	After		Before	After	
	Mean (SD)	Mean (SD)	Diff	Mean (SD)	Mean (SD)	Diff
Medicaid	0.19 (0.39)	0.36 (0.48)	0.17	0.07 (0.26)	0.09 (0.28)	0.02
Employer Sponsored Insurance	0.20 (0.40)	0.22 (0.41)	0.02	0.25 (0.43)	0.28 (0.45)	0.03
Non-Group Private Insurance	0.18 (0.38)	0.20 (0.40)	0.02	0.20 (0.40)	0.30 (0.46)	0.10
Uninsurance Rate	0.44 (0.50)	0.23 (0.42)	-0.21	0.48 (0.50)	0.34 (0.47)	-0.14

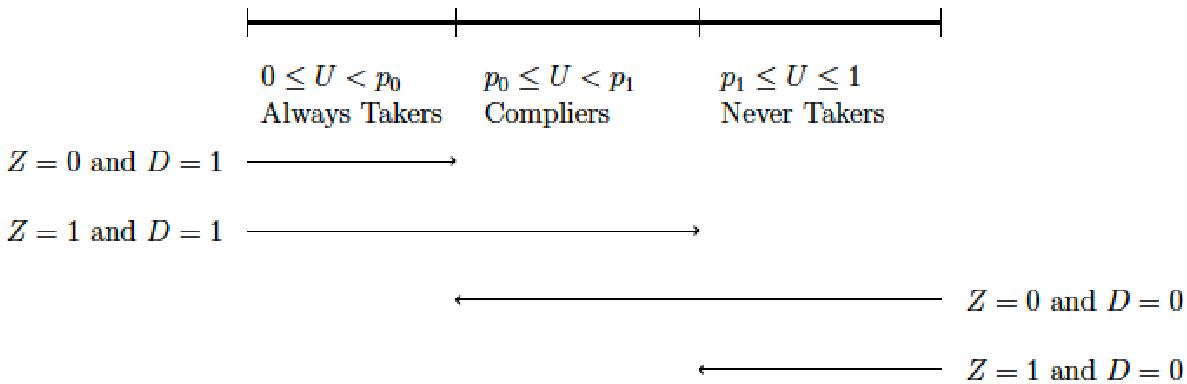
Notes: Means are weighted with ACS weights. Standard errors reported in parentheses

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

	≤138% FPL				≤300% FPL			
	(1) Medicaid	(2) ESI	(3) Purchased	(4) Uninsured	(5) Medicaid	(6) ESI	(7) Purchased	(8) Uninsured
Expanded	0.157***	-0.017***	-0.046***	-0.092***	0.102***	-0.012**	-0.028***	-0.059***
	(0.016)	(0.005)	(0.007)	(0.016)	(0.011)	(0.005)	(0.007)	(0.014)
Observations	706361	706361	706361	706361	1934005	1934005	1934005	1934005
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓

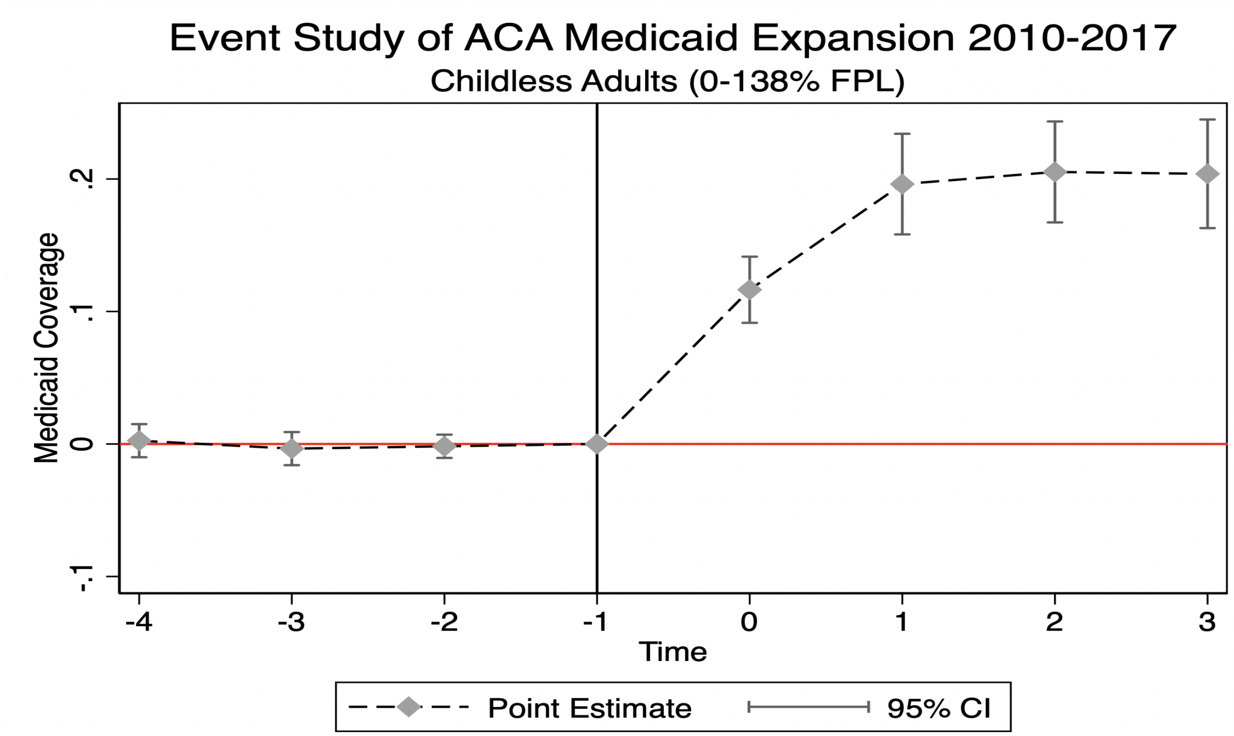
Notes: Sample is restricted to non-disabled childless adults aged 26-64. Standard errors are clustered at the state-year level and are provided in parentheses (*** p<0.01, ** p<0.05, * p<0.10). Each cell reports the results from regressing the main effects of policy variables outlined in equation (6) 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.

Figure 1: Treatment Groups from Complier Analysis



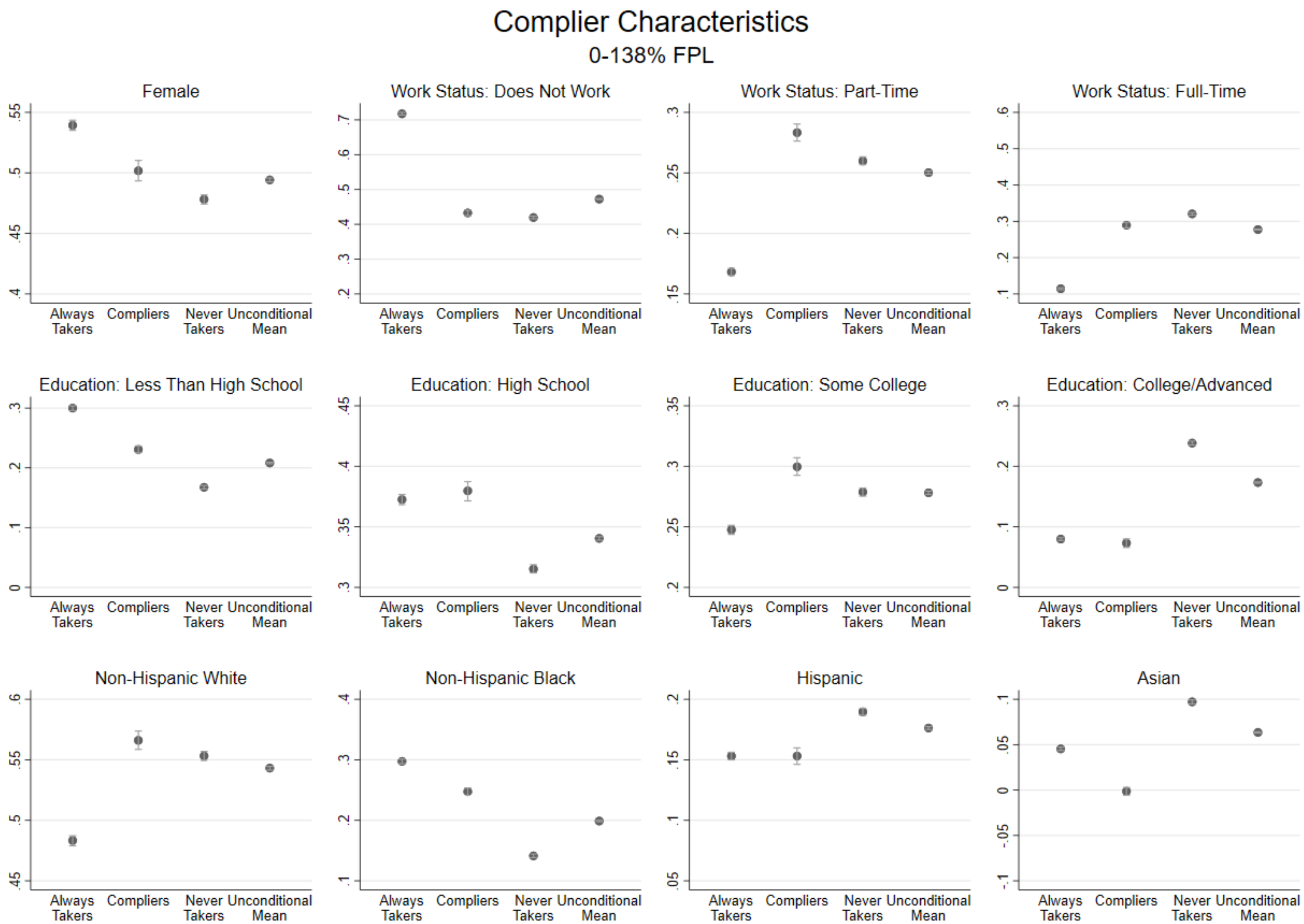
Source: Abrigo et al. (2021)

Figure 2: Event Study of the ACA Medicaid Expansion: Childless Adults (138% FPL)



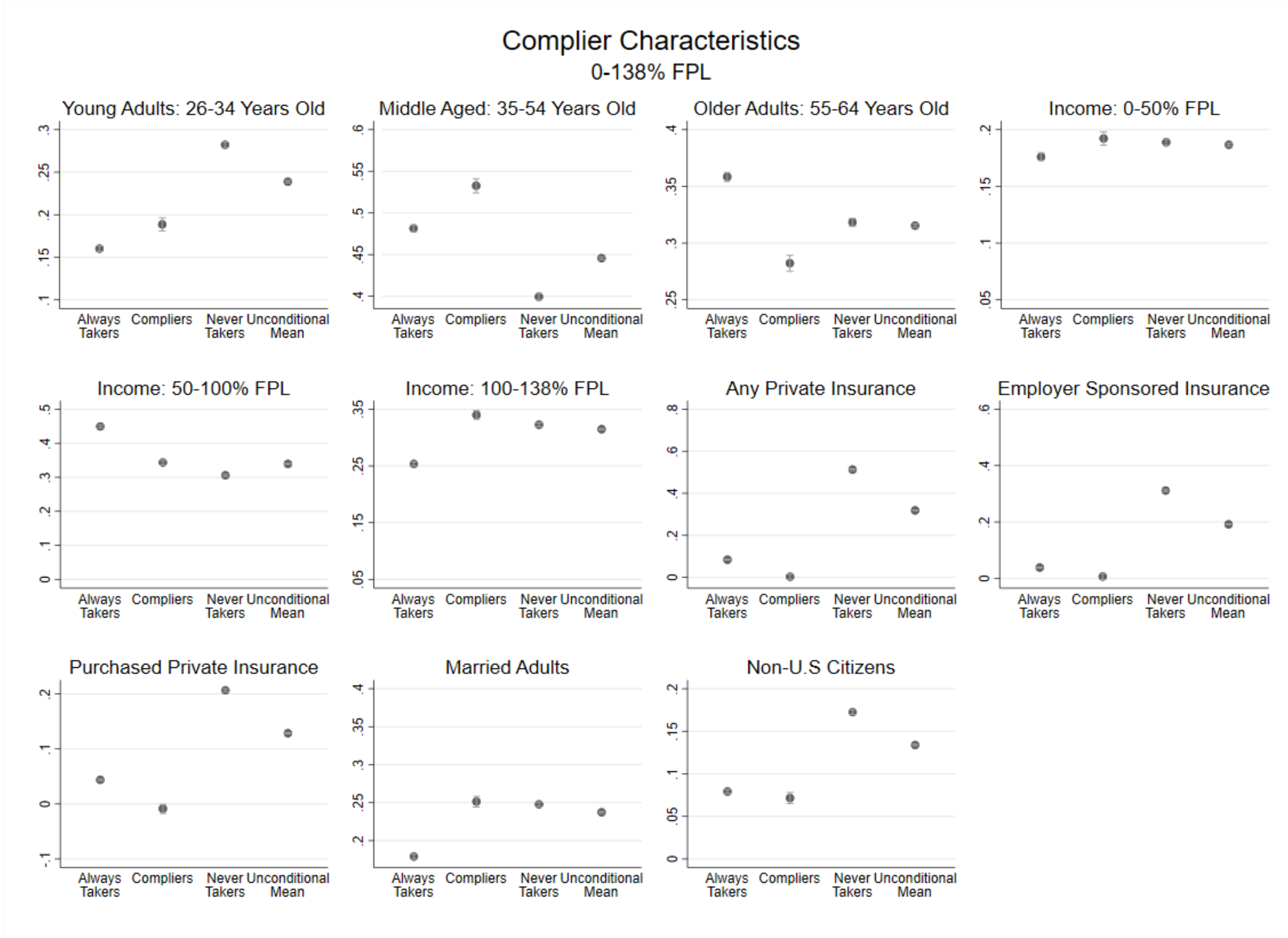
Notes: This figure reports the coefficients from estimating equation (7) with Medicaid coverage as the outcome variable. The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include 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 Always Takers, Compliers and Never Takers: Gender, Work Status, Education, Race, 0-138% FPL



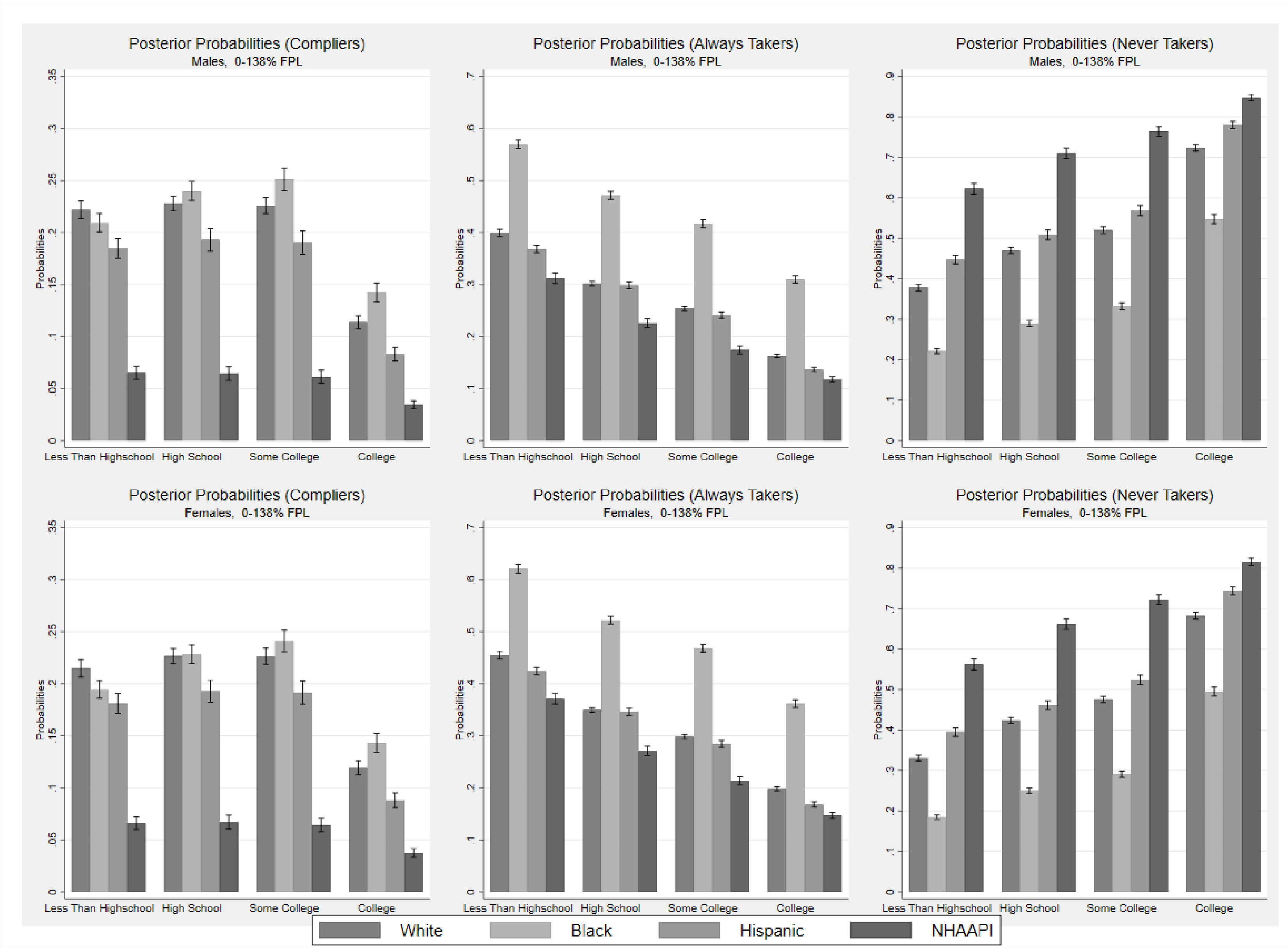
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

Figure 4: Observable Characteristics for Always Takers, Compliers and Never Takers: Age Group, Income Group, Marital Status, Citizenship, 0-138% FPL



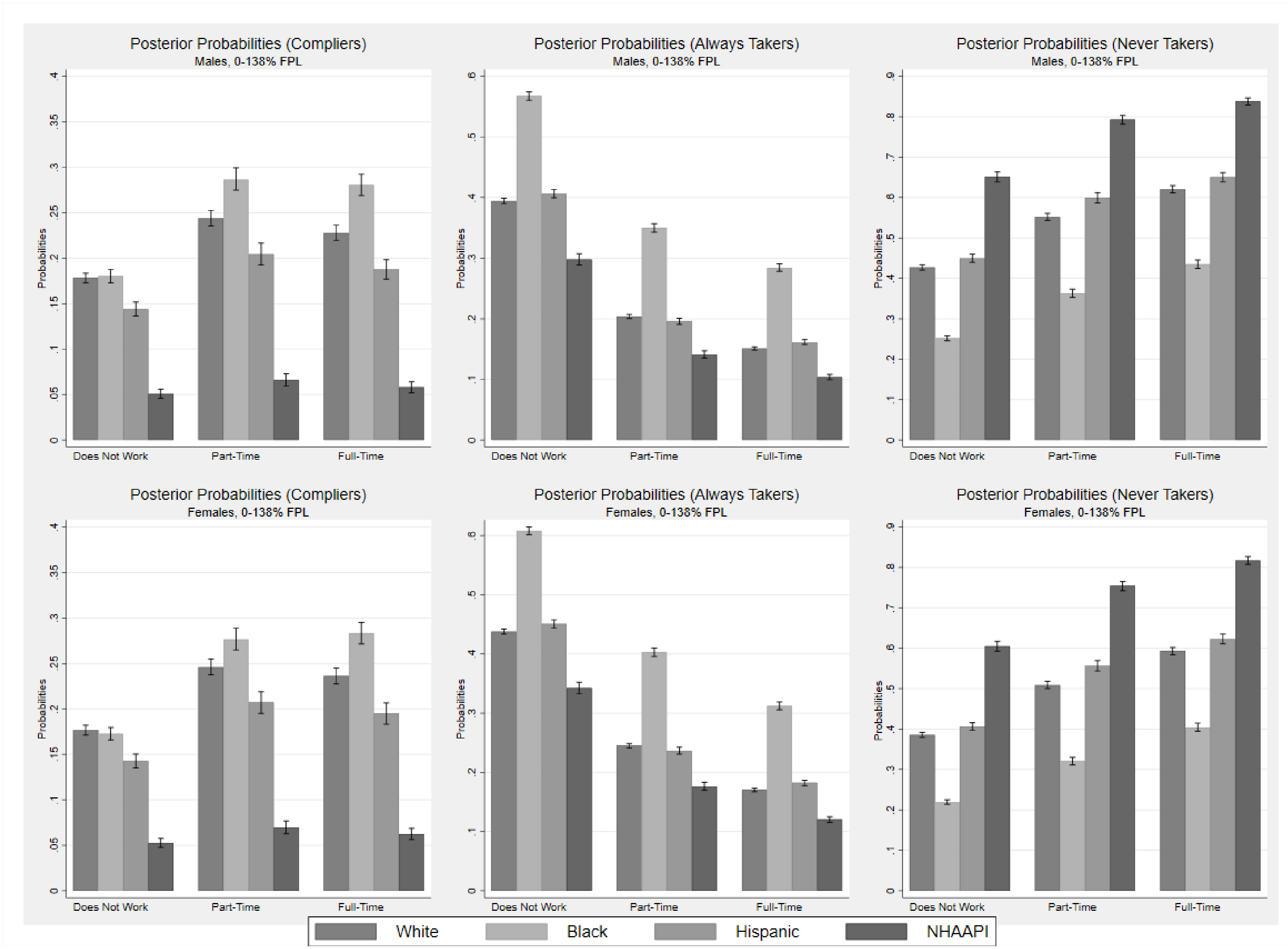
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

Figure 5: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Education, Race, 0-138% FPL



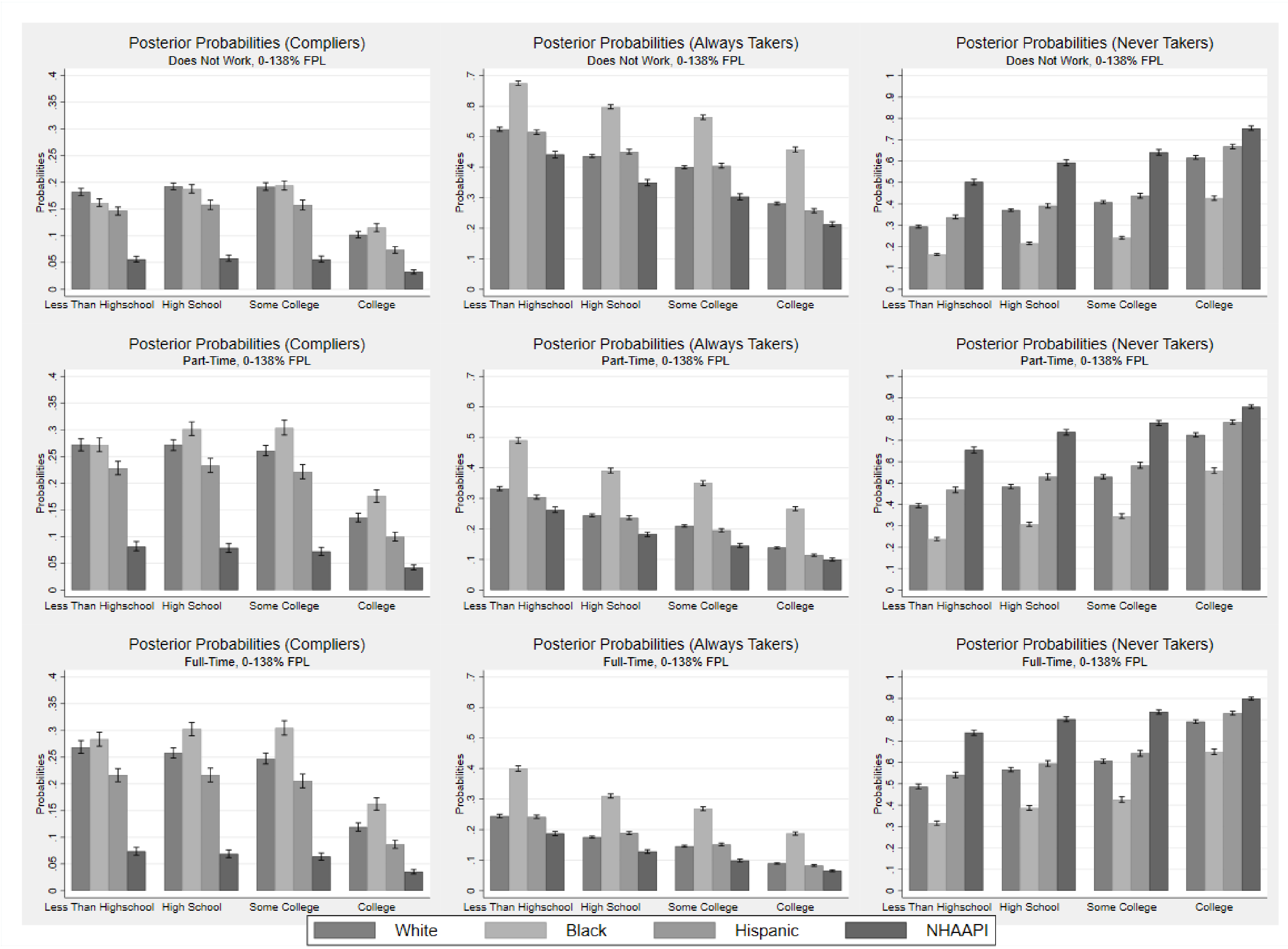
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure 6: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Work Status, Race, 0-138% FPL



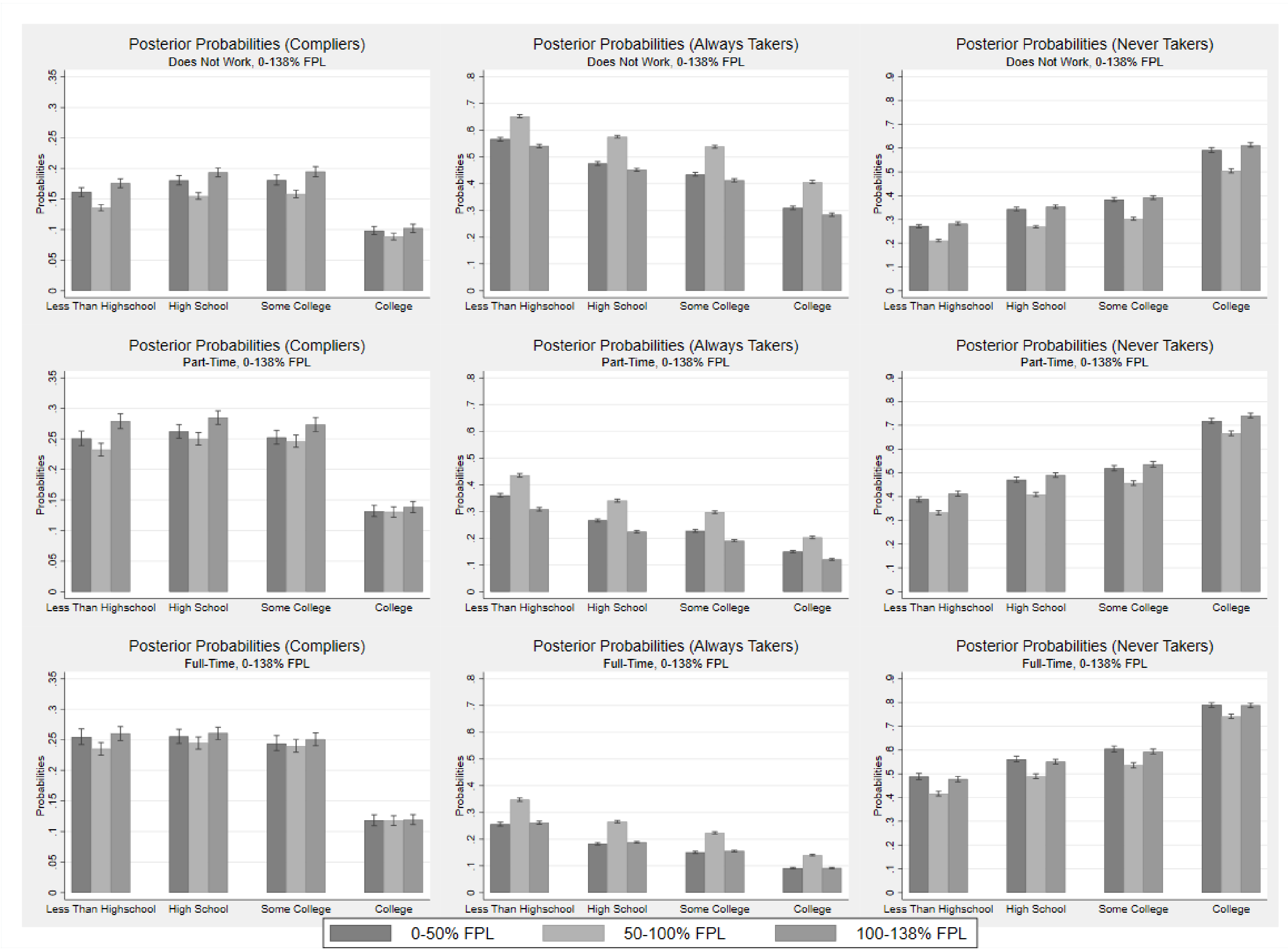
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure 7: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Work Status, Education, Race, 0-138% FPL



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

Figure 8: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Work Status, Education, Income Group, 0-138% FPL



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

Appendix A Tables and Figures

Table A1: Summary Statistics of Control Variables by States' Expansion Status (0-300% 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)	0.49	(0.50)	0.49	(0.50)	0.49	(0.50)
Age (years)	45.99	(11.96)	45.90	(12.34)	46.36	(11.73)	46.20	(12.07)
Income (% of FPL)	164.62	(88.04)	165.29	(88.30)	167.82	(85.76)	168.11	(85.78)
Married	0.31	(0.46)	0.30	(0.46)	0.34	(0.47)	0.32	(0.47)
U.S. Citizen	0.86	(0.34)	0.87	(0.34)	0.90	(0.30)	0.89	(0.32)
Household Size	2.19	(1.15)	2.22	(1.18)	2.09	(1.02)	2.12	(1.05)
Race								
Non-Hispanic White	0.59	(0.49)	0.57	(0.49)	0.60	(0.49)	0.55	(0.50)
Non-Hispanic Black	0.13	(0.33)	0.14	(0.35)	0.21	(0.41)	0.23	(0.42)
Hispanic	0.18	(0.39)	0.19	(0.39)	0.15	(0.36)	0.18	(0.38)
AANHPI	0.08	(0.27)	0.08	(0.28)	0.03	(0.17)	0.03	(0.18)
Education								
Less than High School	0.16	(0.37)	0.16	(0.36)	0.17	(0.38)	0.17	(0.37)
High School	0.33	(0.47)	0.33	(0.47)	0.37	(0.48)	0.36	(0.48)
Some College	0.31	(0.46)	0.30	(0.46)	0.30	(0.46)	0.30	(0.46)
College or Advanced	0.20	(0.40)	0.20	(0.40)	0.16	(0.37)	0.17	(0.38)
Employment								
Hours Worked Last Year	25.03	(19.67)	25.79	(19.55)	26.80	(19.71)	27.21	(19.67)
Does Not Work	0.31	(0.46)	0.29	(0.46)	0.29	(0.45)	0.28	(0.45)
Part-Time	0.21	(0.41)	0.21	(0.41)	0.19	(0.39)	0.18	(0.38)
Full-Time	0.48	(0.50)	0.50	(0.50)	0.53	(0.50)	0.54	(0.50)

Notes: Means are weighted with ACS weights

Table A2: Mean Differences in Health Insurance Outcomes Before and After the ACA Medicaid Expansion in Expansion and Non-Expansion States by Race/Ethnicity (0-300% 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	0.12 (0.33)	0.25 (0.43)	0.13	0.07 (0.25)	0.09 (0.28)	0.02
Employer Sponsored Insurance	0.38 (0.49)	0.39 (0.49)	0.01	0.39 (0.49)	0.40 (0.49)	0.01
Non-Group Private Insurance	0.11 (0.32)	0.14 (0.35)	0.03	0.11 (0.31)	0.16 (0.37)	0.05
Uninsurance Rate	0.37 (0.48)	0.21 (0.41)	-0.16	0.41 (0.49)	0.32 (0.47)	-0.09

	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	0.10 (0.30)	0.22 (0.42)	0.12	0.06 (0.23)	0.08 (0.26)	0.02
Employer Sponsored Insurance	0.42 (0.49)	0.42 (0.49)	0.00	0.43 (0.49)	0.43 (0.49)	0.00
Non-Group Private Insurance	0.14 (0.35)	0.17 (0.38)	0.03	0.13 (0.34)	0.19 (0.39)	0.06
Uninsurance Rate	0.33 (0.47)	0.17 (0.38)	-0.16	0.36 (0.48)	0.28 (0.45)	-0.08

	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	0.20 (0.40)	0.33 (0.47)	0.13	0.11 (0.32)	0.13 (0.34)	0.02
Employer Sponsored Insurance	0.36 (0.48)	0.39 (0.49)	0.03	0.39 (0.49)	0.43 (0.49)	0.04
Non-Group Private Insurance	0.06 (0.24)	0.09 (0.29)	0.03	0.07 (0.26)	0.12 (0.32)	0.05
Uninsurance Rate	0.37 (0.48)	0.19 (0.39)	-0.18	0.41 (0.49)	0.30 (0.46)	-0.11

	Hispanic Low-Income Individuals					
	Expansion States			Non-Expansion States		
	Before	After		Before	After	
	Mean (SD)	Mean (SD)	Diff	Mean (SD)	Mean (SD)	Diff
Medicaid	0.13 (0.34)	0.26 (0.44)	0.13	0.06 (0.23)	0.07 (0.25)	0.01
Employer Sponsored Insurance	0.30 (0.46)	0.33 (0.47)	0.03	0.27 (0.45)	0.32 (0.47)	0.05
Non-Group Private Insurance	0.05 (0.22)	0.08 (0.28)	0.03	0.05 (0.22)	0.13 (0.33)	0.08
Uninsurance Rate	0.52 (0.50)	0.32 (0.47)	-0.20	0.62 (0.49)	0.48 (0.50)	-0.14

	AANHPI Low-Income Individuals					
	Expansion States			Non-Expansion States		
	Before	After		Before	After	
	Mean (SD)	Mean (SD)	Diff	Mean (SD)	Mean (SD)	Diff
Medicaid	0.13 (0.33)	0.26 (0.44)	0.13	0.05 (0.22)	0.06 (0.23)	0.01
Employer Sponsored Insurance	0.35 (0.48)	0.37 (0.48)	0.02	0.38 (0.48)	0.41 (0.49)	0.03
Non-Group Private Insurance	0.15 (0.36)	0.20 (0.40)	0.05	0.16 (0.37)	0.28 (0.45)	0.14
Uninsurance Rate	0.38 (0.48)	0.19 (0.39)	-0.19	0.41 (0.49)	0.26 (0.44)	-0.15

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

Table A3: Event Study Results of Expansion on Medicaid Coverage for Childless Adults

	≤138% FPL			≤300% FPL		
	(1) Medicaid	(2) Private	(3) Uninsured	(4) Medicaid	(5) Private	(6) Uninsured
Year -4	0.003	-0.005	0.001	0.000	0.003	-0.001
	(0.006)	(0.005)	(0.008)	(0.003)	(0.005)	(0.004)
Year -3	-0.003	0.003	-0.005	0.001	0.005	-0.005*
	(0.006)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)
Year -2	-0.002	-0.007	0.006	-0.001	-0.001	0.002
	(0.004)	(0.005)	(0.006)	(0.002)	(0.003)	(0.003)
Year 0	0.116***	-0.055***	-0.058***	0.074***	-0.028***	-0.042***
	(0.012)	(0.006)	(0.015)	(0.006)	(0.007)	(0.010)
Year 1	0.196***	-0.079***	-0.112***	0.123***	-0.044***	-0.072***
	(0.019)	(0.007)	(0.021)	(0.010)	(0.008)	(0.015)
Year 2	0.205***	-0.086***	-0.127***	0.136***	-0.052***	-0.084***
	(0.019)	(0.008)	(0.021)	(0.010)	(0.007)	(0.014)
Year 3	0.204***	-0.078***	-0.117***	0.136***	-0.045***	-0.083***
	(0.020)	(0.007)	(0.020)	(0.012)	(0.008)	(0.015)
Observations	621509	621509	621509	1723030	1723030	1723030
Year FEs	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓

Notes: The 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 (7) 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.

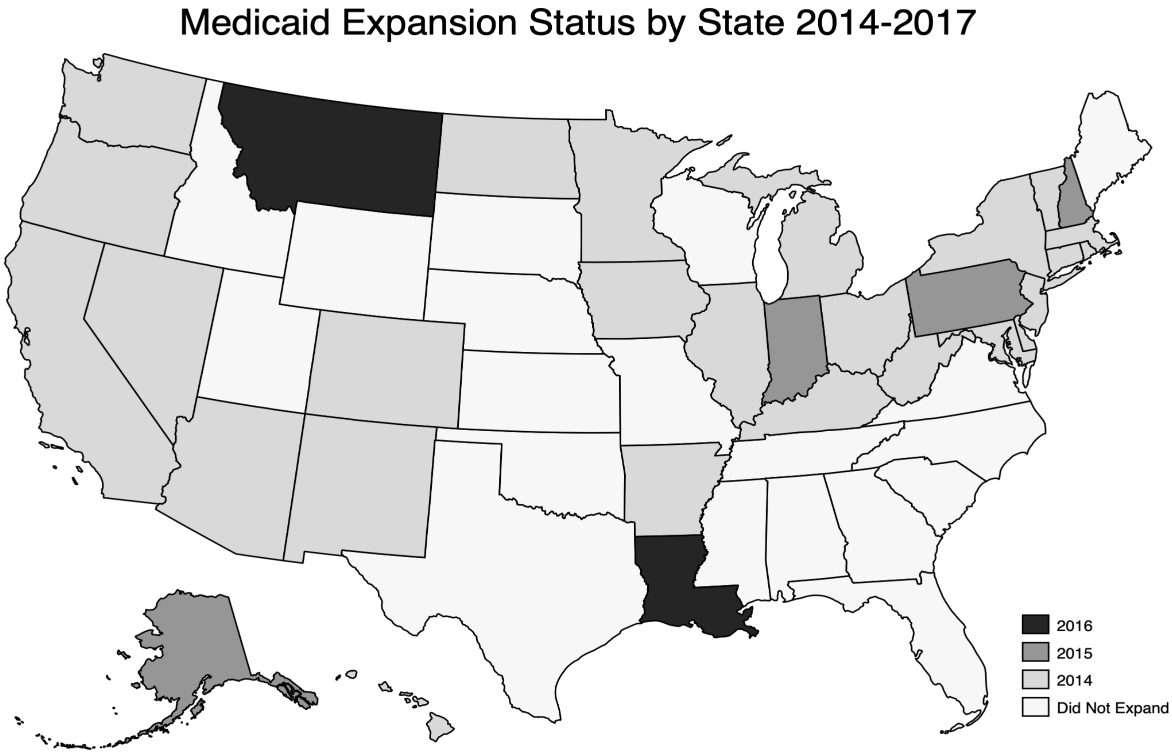
Table A4: Observable Characteristics for Always Takers, Compliers and Never Takers 0-138% FPL

	(1) AT	(2) C	(3) NT	(4) Mean
Main Demographics				
Female	53.9	50.2	47.8	49.4
Married	17.9	25.1	24.8	23.7
Non-U.S. Citizen	7.9	7.2	17.3	13.4
Race				
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
AANHPI	4.5	0.0	9.7	6.3
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
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
Private Insurance				
Any Private	8.4	0.0	51.3	31.9
Employer Sponsored Health Insurance	3.8	0.0	31.2	19.2
Non-Group Private Insurance	4.4	0.0	20.7	12.9
Age Group				
25-34 Years Old	16.0	18.9	28.2	23.9
35-54 Years Old	48.1	53.3	39.9	44.6
55-64 Years Old	35.8	28.2	31.8	31.5
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 A5: Observable Characteristics for Always Takers, Compliers and Never Takers 0-300% FPL

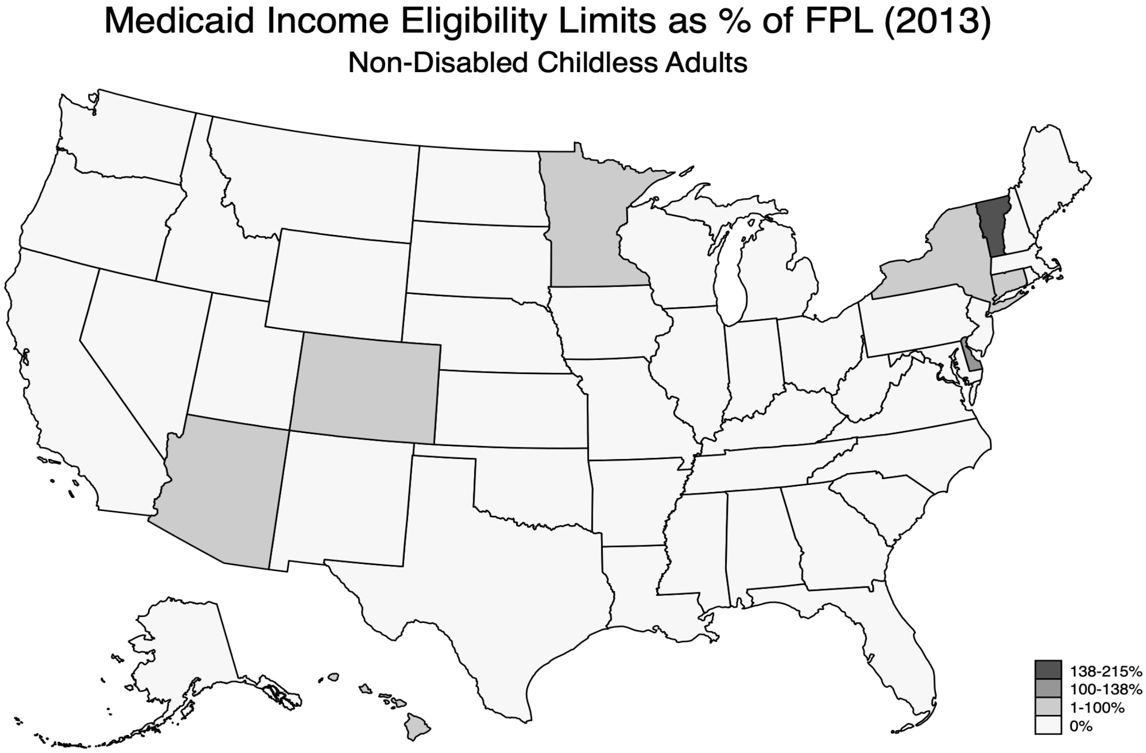
	(1) AT	(2) C	(3) NT	(4) Mean
Main Demographics				
Female	53.0	50.5	48.0	48.9
Married	22.9	37.2	31.8	31.6
Non-U.S. Citizen	8.8	3.9	13.6	12.1
Race				
Non-Hispanic White	49.1	58.5	59.5	57.8
Non-Hispanic Black	27.9	34.4	12.3	17.1
Hispanic	16.0	11.3	18.6	17.8
AANHPI	5.1	−6.4	8.1	5.9
Education				
Less Than High School	27.9	22.8	13.5	16.4
High School	37.6	41.3	32.9	34.6
Some College	25.6	30.5	31.0	30.4
College/Advanced	9.0	2.7	22.6	18.6
Work Status				
Does Not Work	64.6	36.8	23.3	29.3
Part-Time	17.7	23.6	19.1	19.7
Full-Time	17.7	39.4	57.6	51.0
Private Insurance				
Any Private	11.2	−7.0	68.5	51.8
Employer Sponsored Health Insurance	6.2	1.9	51.2	39.3
Non-Group Private Insurance	5.2	−8.8	18.1	13.2
Age Group				
25-34 Years Old	16.8	13.2	27.8	24.7
35-54 Years Old	47.8	60.4	40.0	43.7
55-64 Years Old	35.5	26.6	32.2	31.7
Income Group				
0-50% FPL	11.6	10.9	5.4	6.8
50-100% FPL	29.7	19.6	8.9	12.5
100-138% FPL	16.8	19.4	9.3	11.6
138-200% FPL	17.4	22.3	22.6	22.0
200-250% FPL	9.4	9.6	24.1	20.5
250-300% FPL	7.1	11.8	24.4	20.7

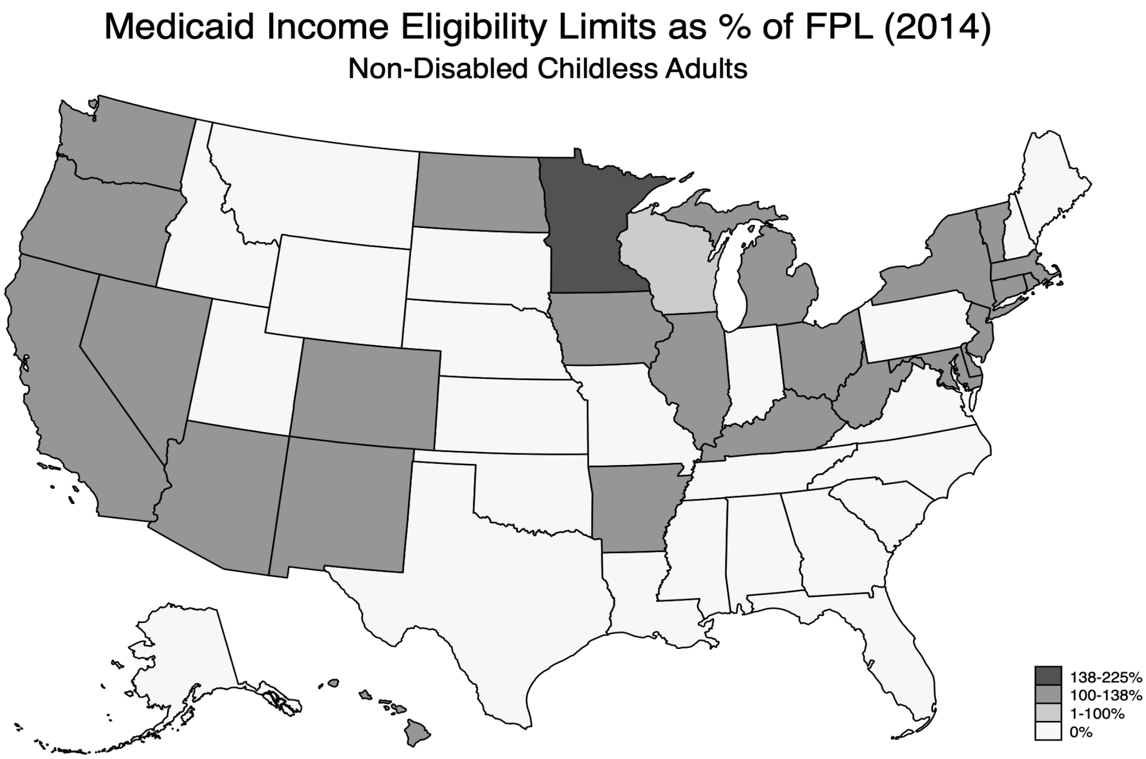
Figure A1: ACA Medicaid Expansion Status (2014-2017)



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

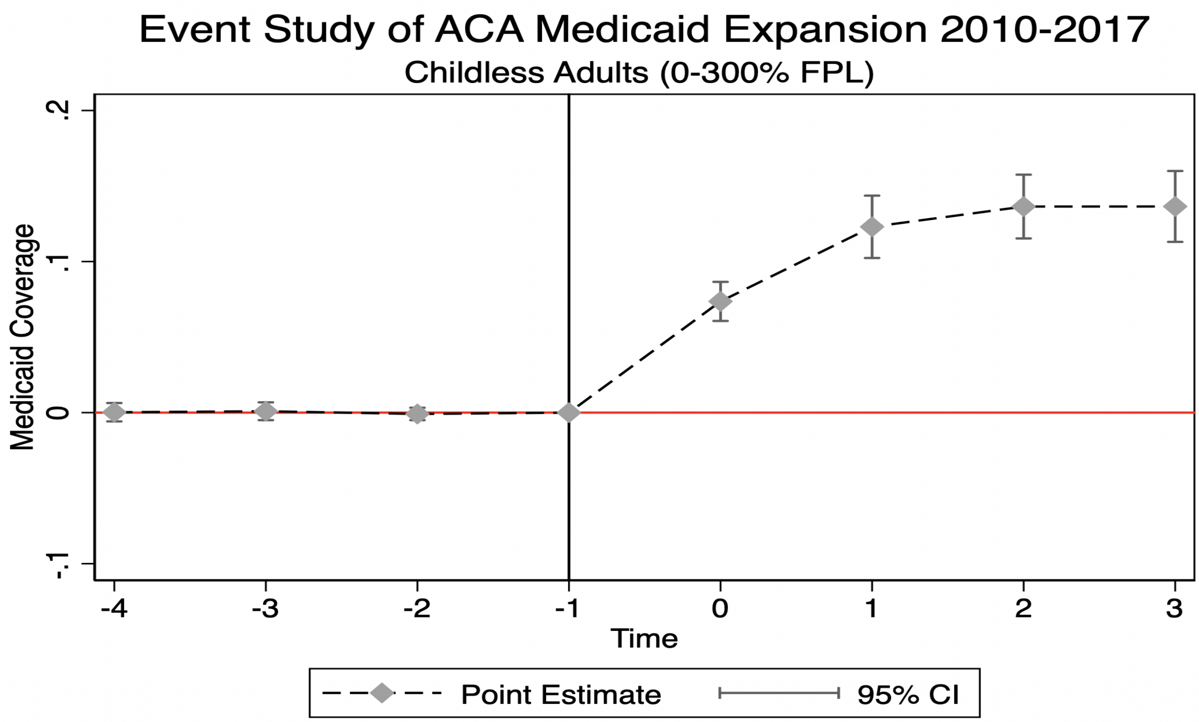
Figure A2: Medicaid Income Eligibility Limits as % of FPL (2013-2014)





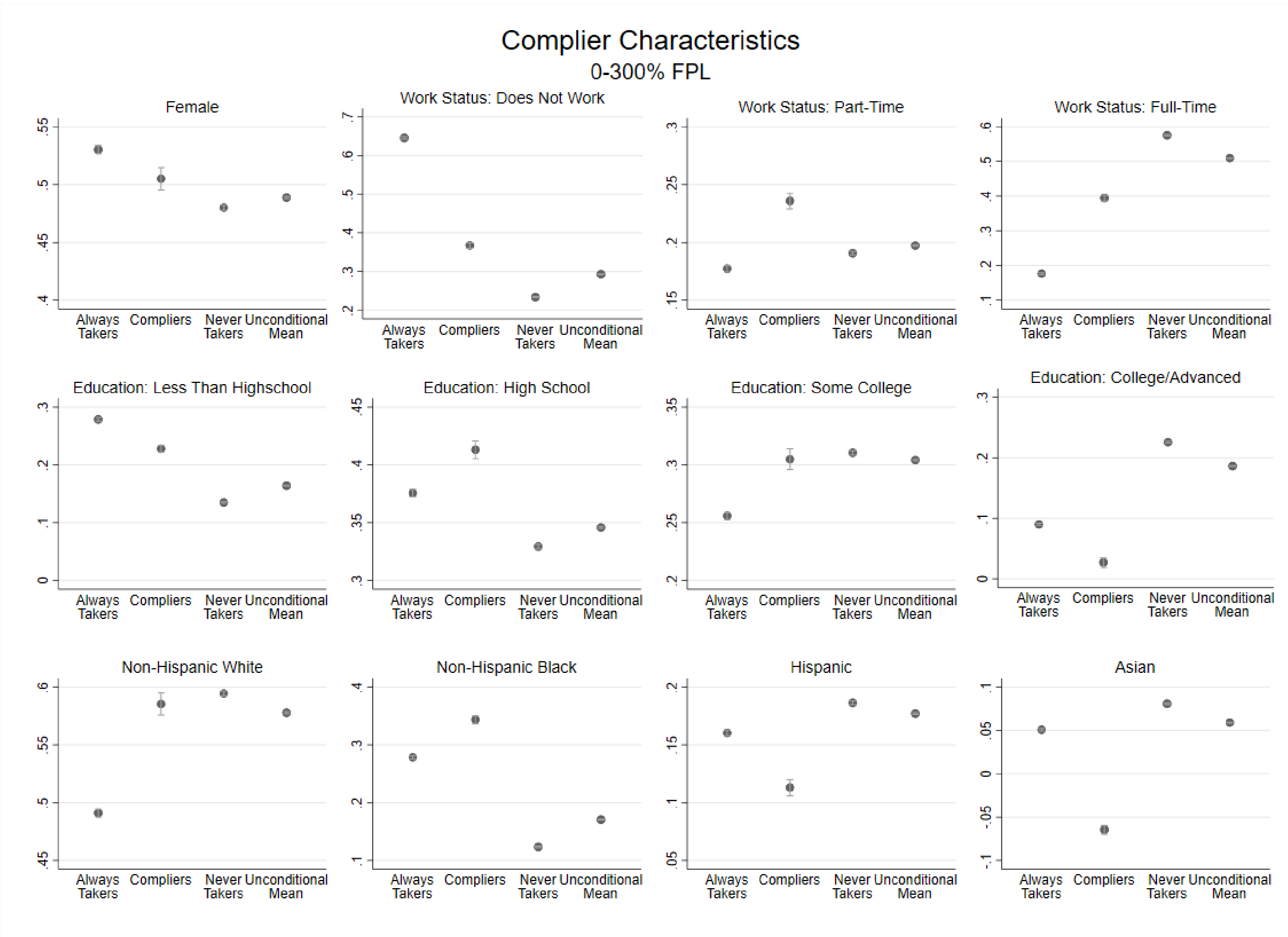
Note: Figure was created by author using information on states' Medicaid eligibility thresholds rates from the Kaiser Family Foundation (KFF).

Figure A3: Event Study of the ACA Medicaid Expansion: Childless Adults (300% FPL)



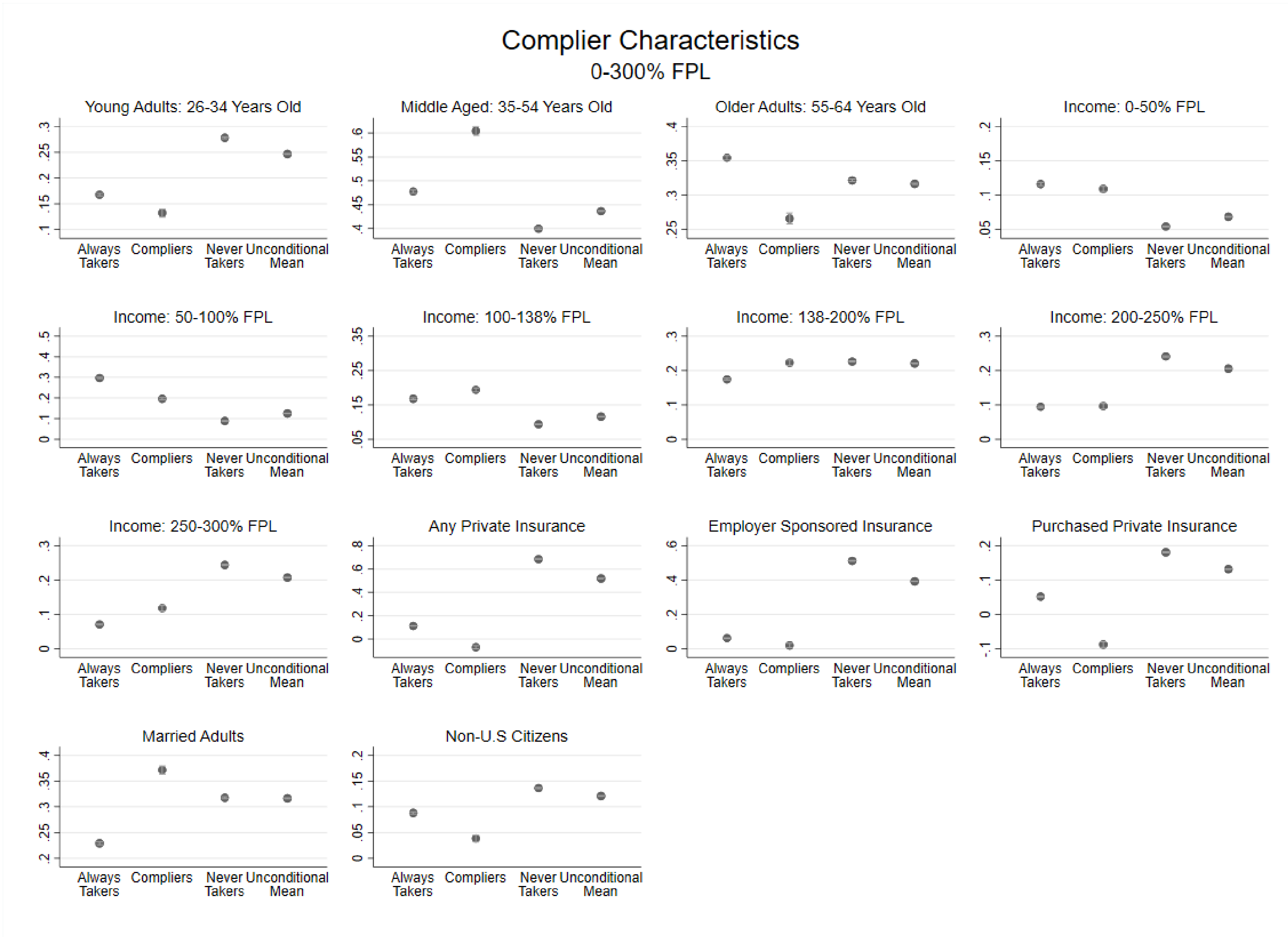
Notes: This figure reports the coefficients from estimating equation (7) with Medicaid coverage as the outcome variable. The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 300% FPL. Controls include 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 A4: Observable Characteristics for Always Takers, Compliers, and Never Takers: Gender, Work Status, Education, Race, 0-300% FPL



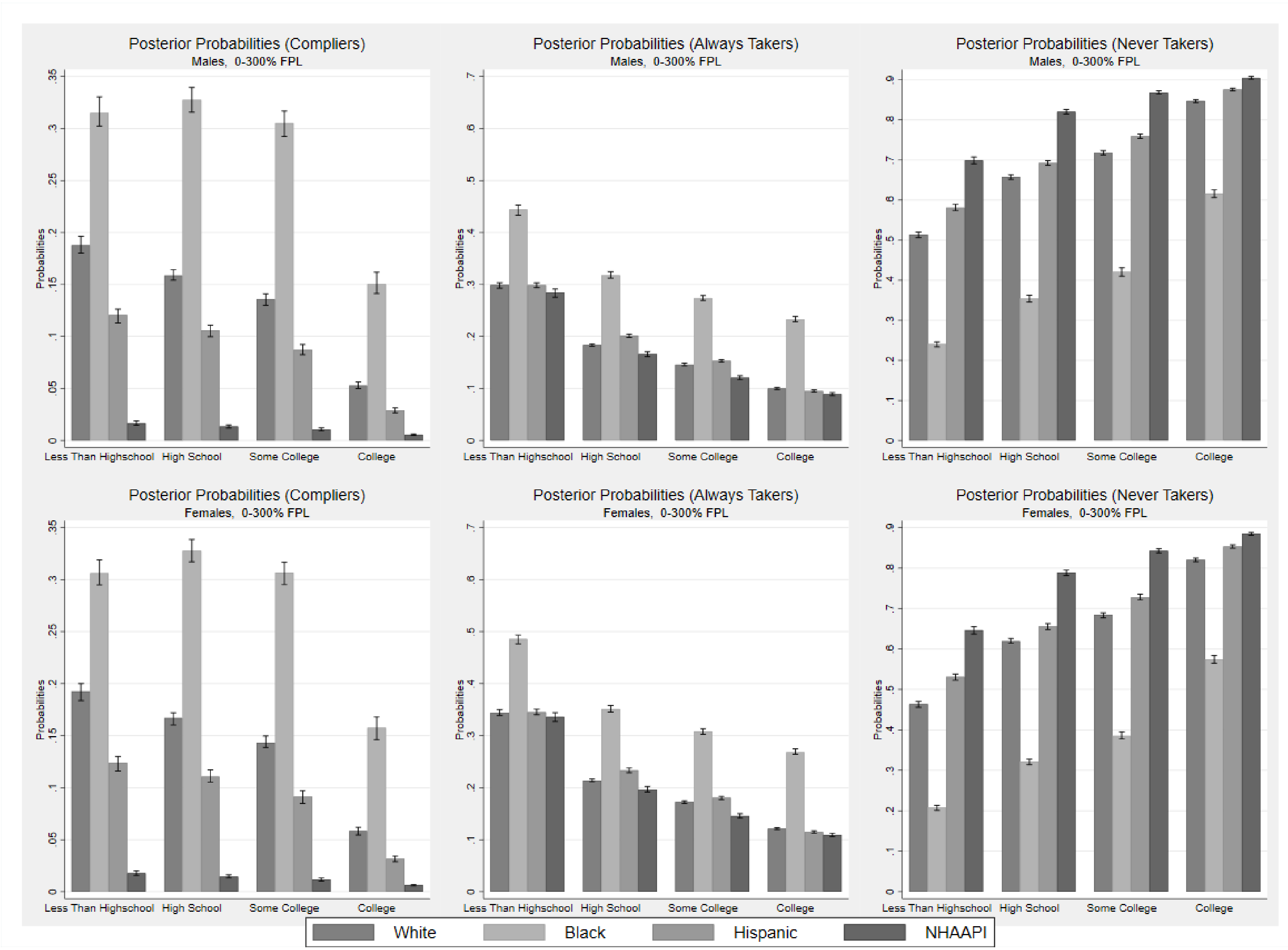
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

Figure A5: Observable Characteristics for Always Takers, Compliers, and Never Takers: Age Group, Income Group, Marital Status, Citizenship, 0-300% FPL



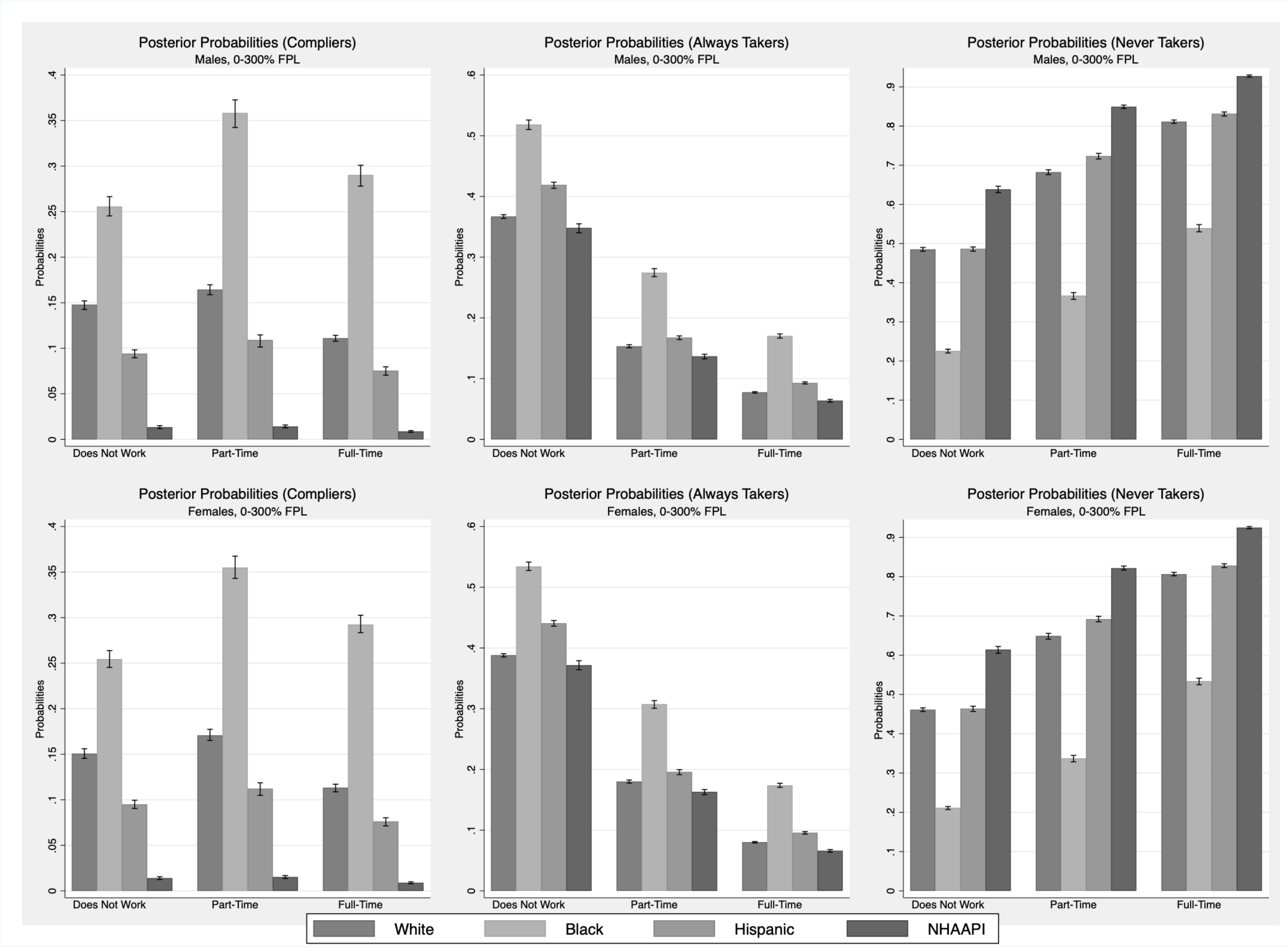
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

Figure A6: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Education, Race, 0-300% FPL



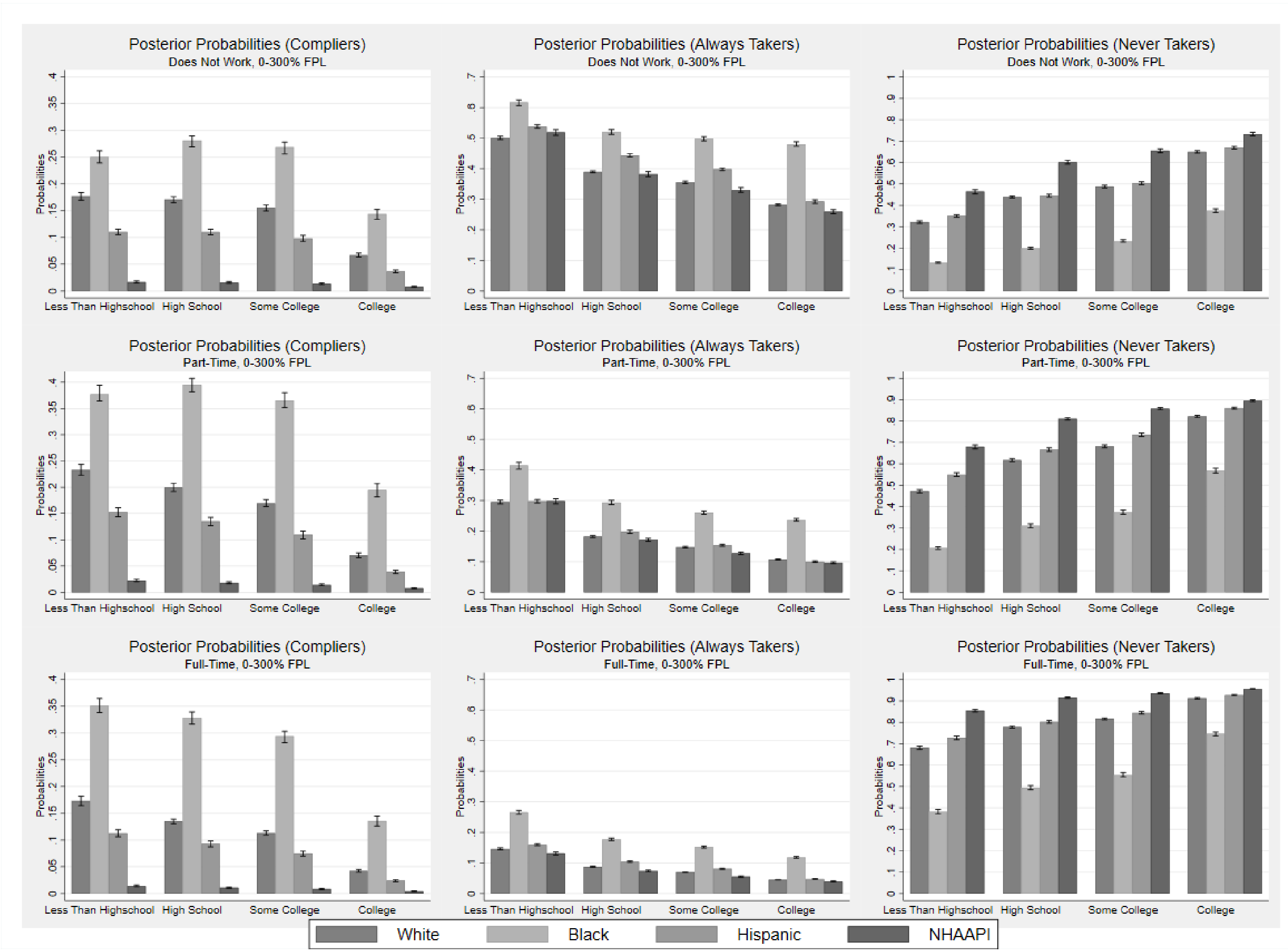
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A7: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Work Status, Race, 0-300% FPL



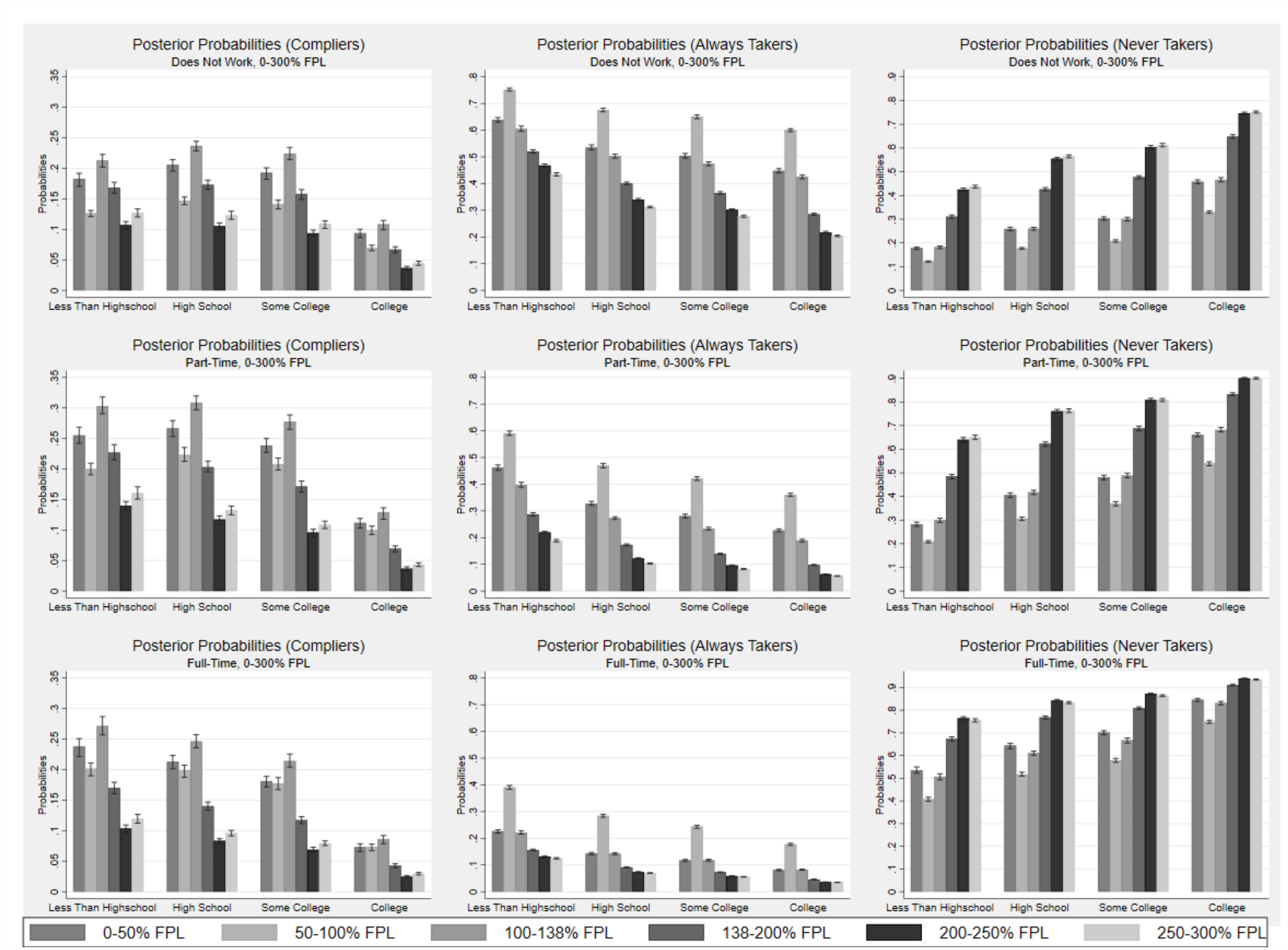
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A8: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Work Status, Education, Race, 0-300% FPL



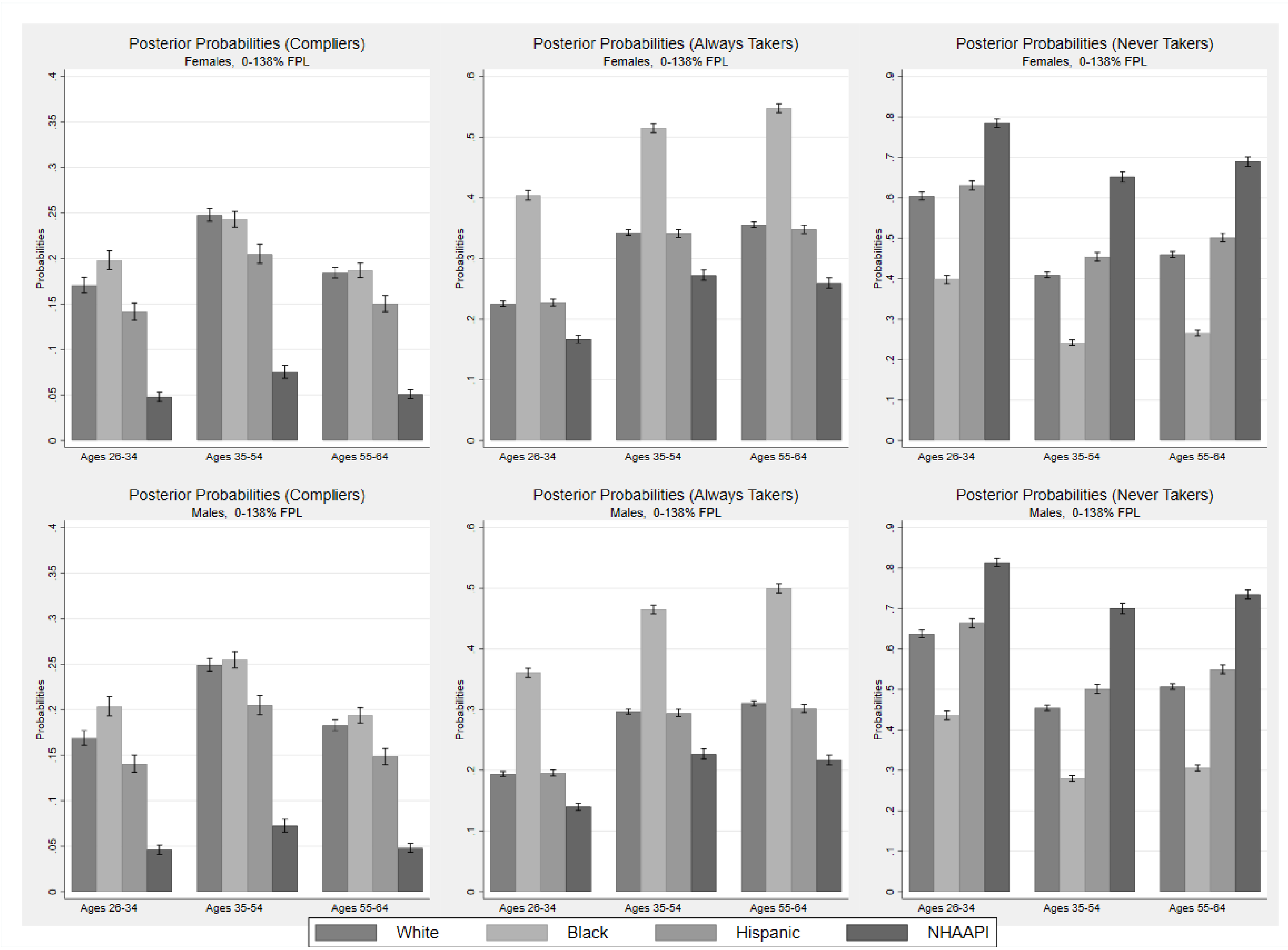
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A9: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Work Status, Education, Income Group, 0-300% FPL



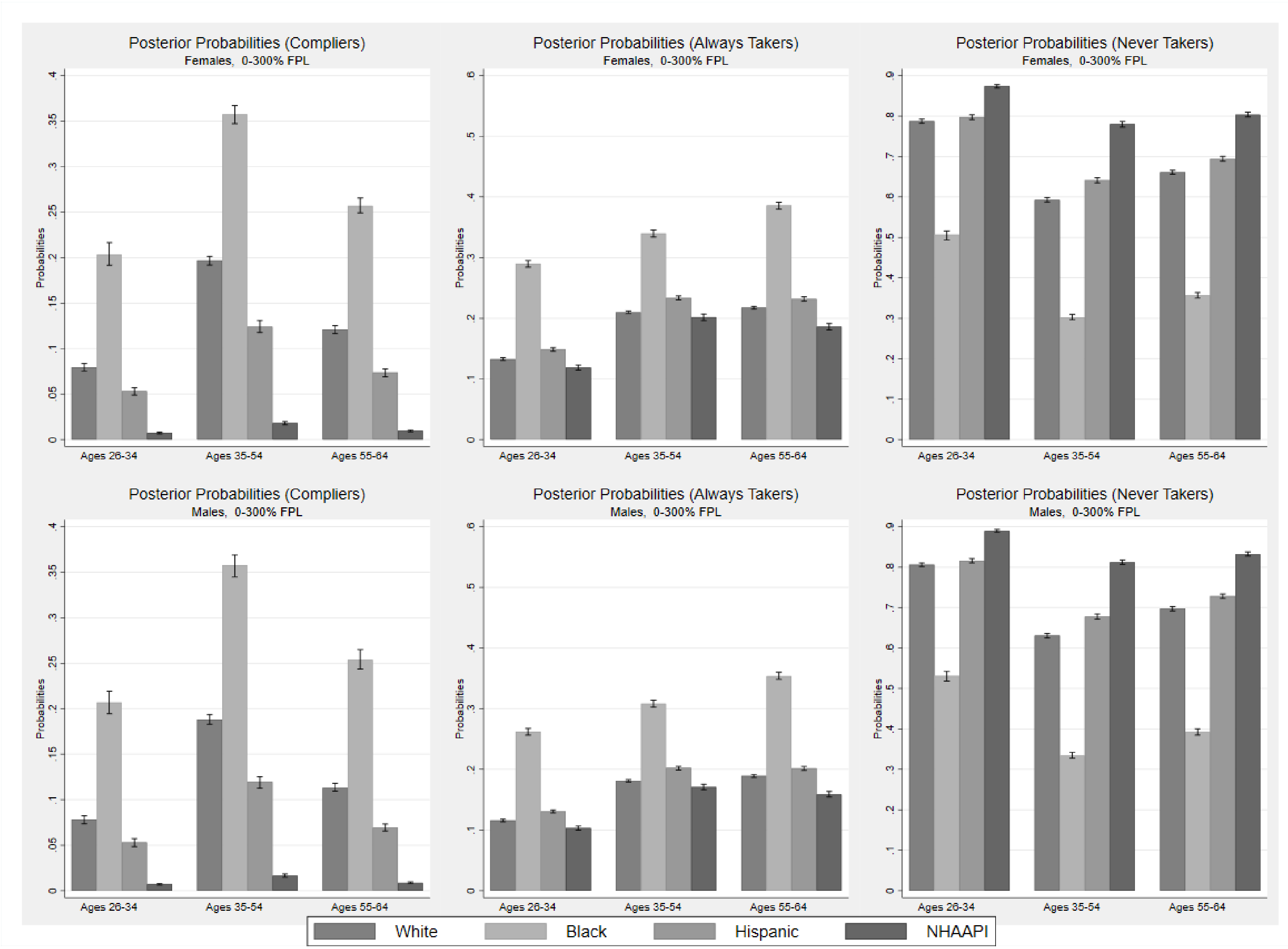
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A10: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Age Group, Race, 0-138% FPL



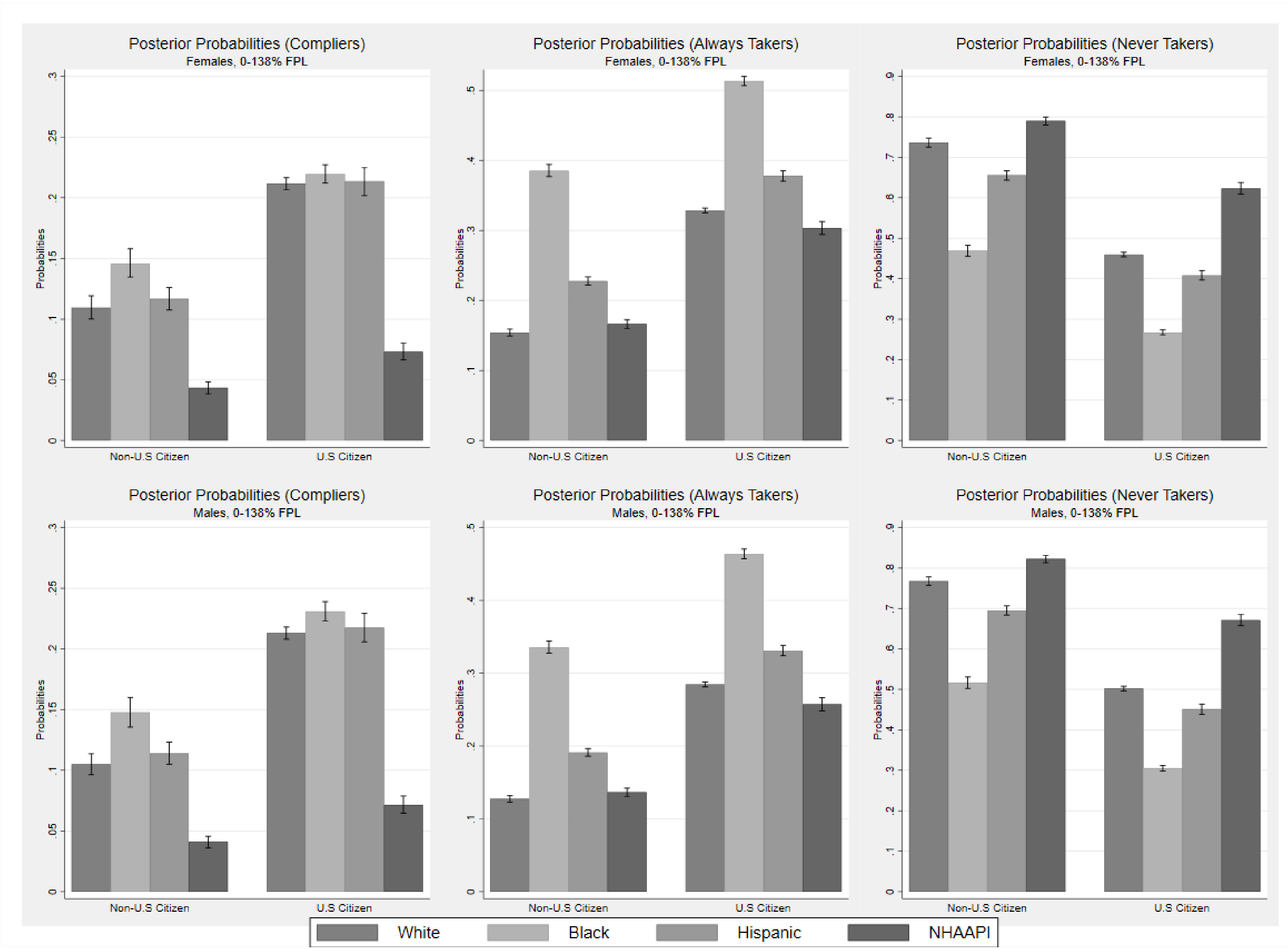
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A11: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Age Group, Race, 0-300% FPL



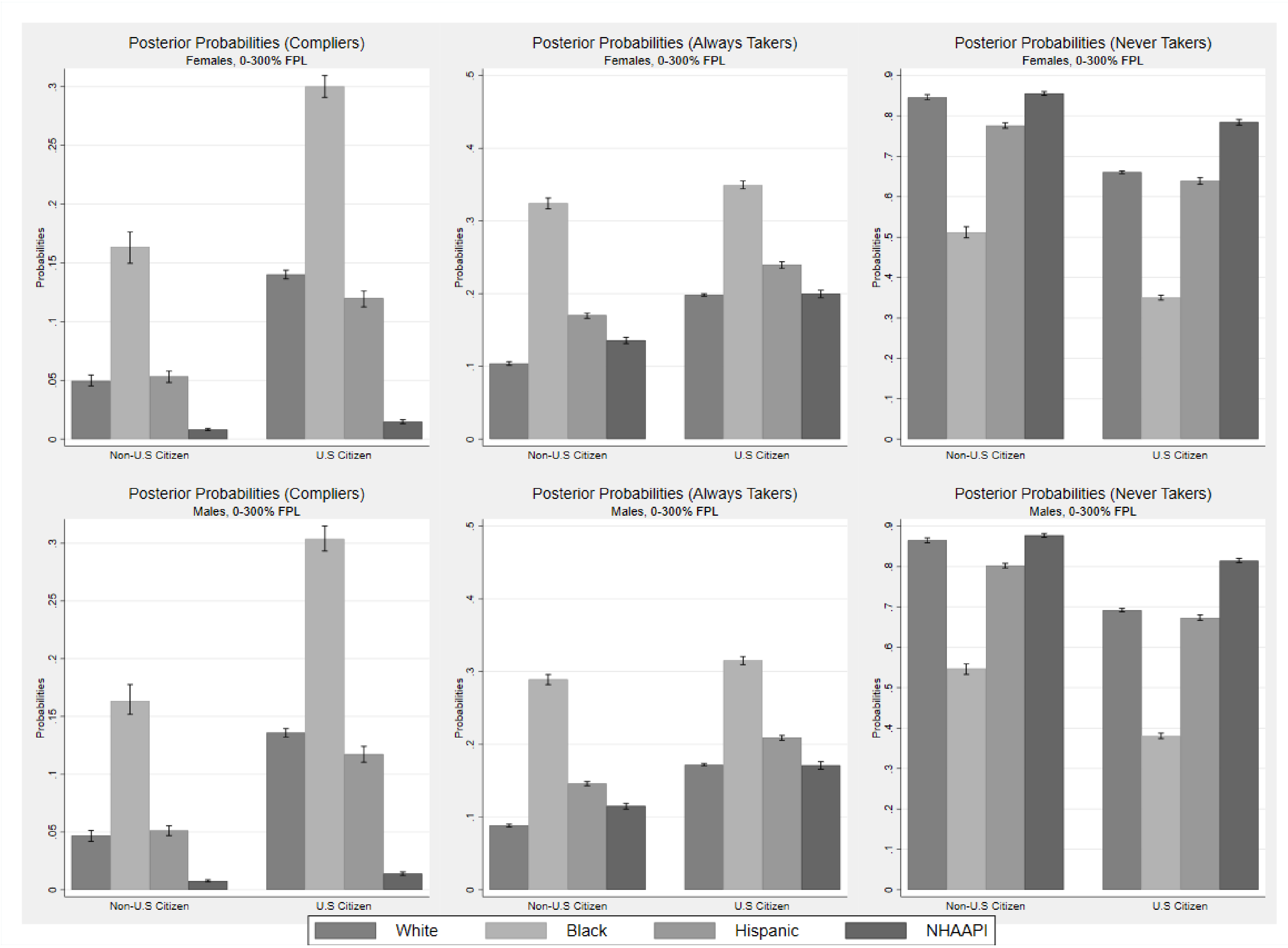
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A12: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Citizenship, Race, 0-138% FPL



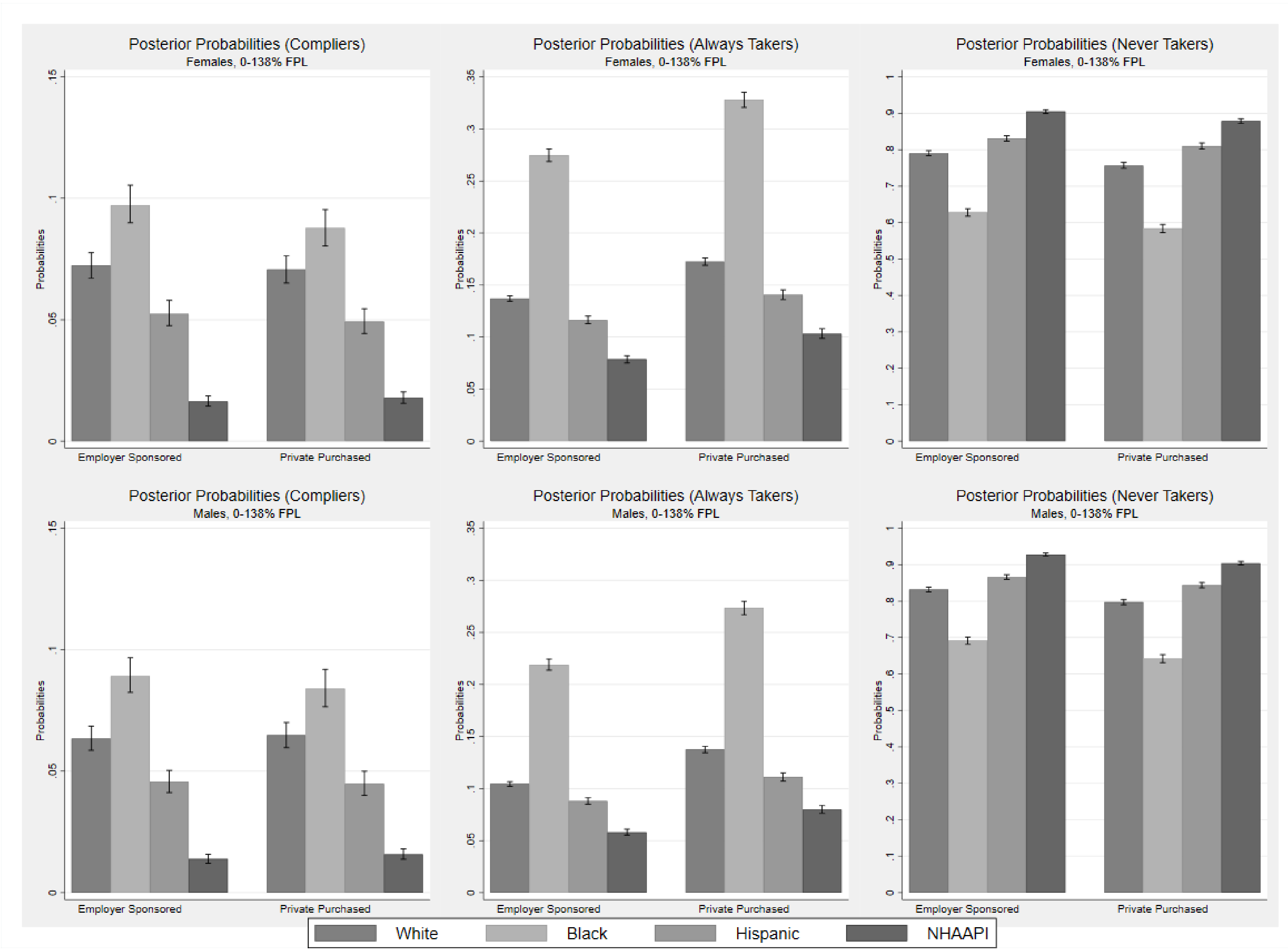
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A13: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Citizenship, Race, 0-300% FPL



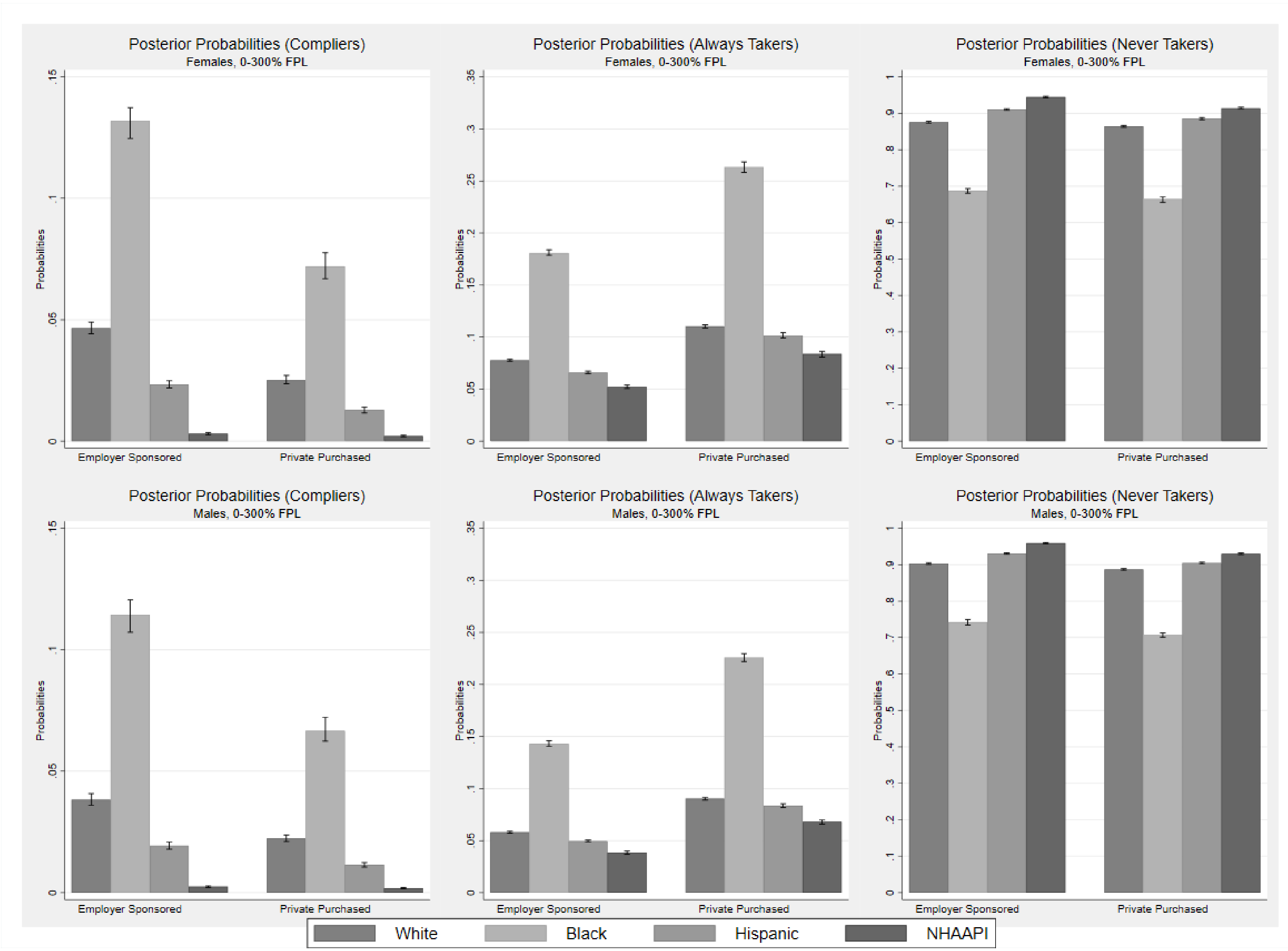
Notes: I computed both the means and 95% confidence intervals from 1000 bootstrapped re-samples.

Figure A14: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Private Insurance, Race, 0-138% FPL



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

Figure A15: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Private Insurance, Race, 0-300% FPL



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

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 employ 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 figures B1 and B2 of 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 to 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). Tables B1 and B2 in the appendix report 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)

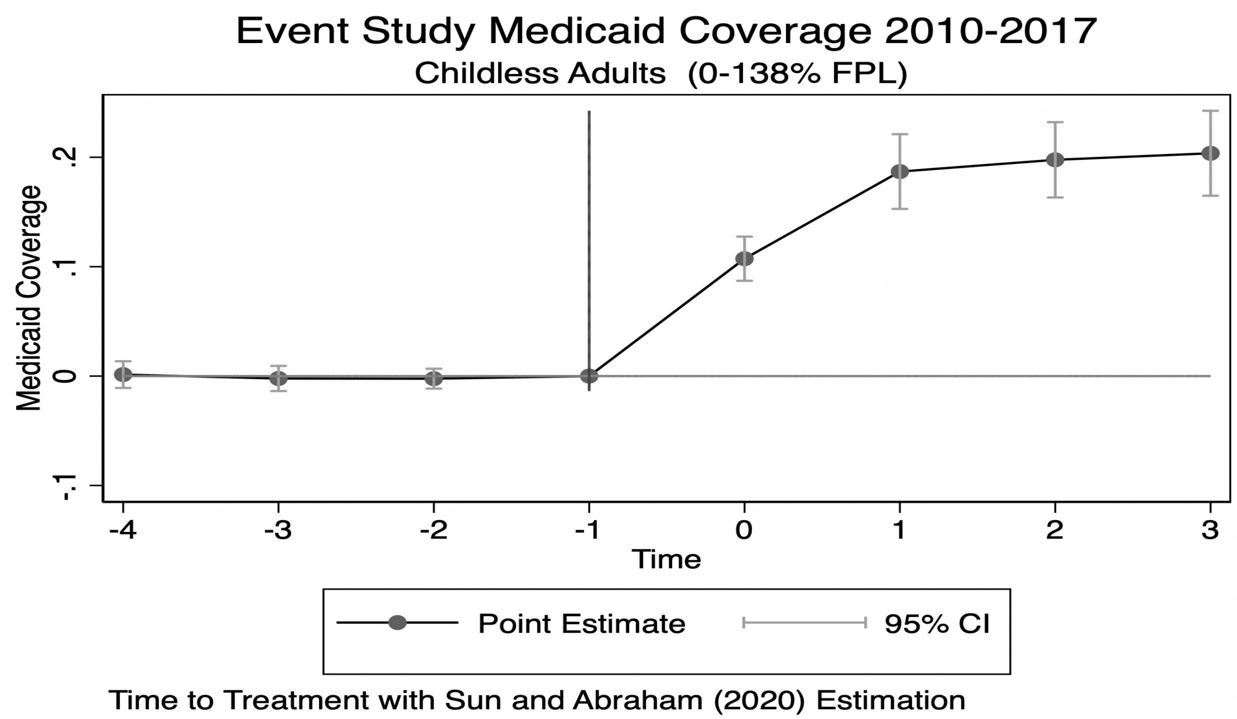
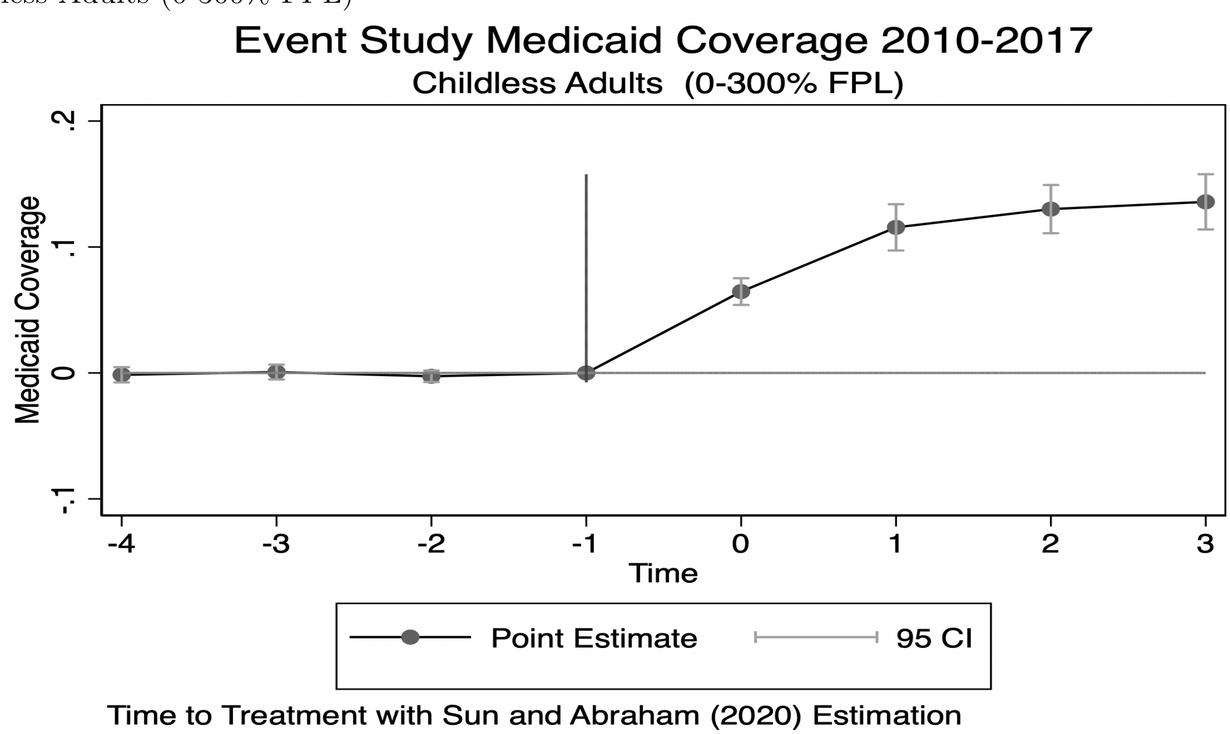


Figure B2: Event Study (Sun and Abraham, 2020) of the ACA Medicaid Expansion: Childless Adults (0-300% FPL)



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 B3: Bacon Decomposition of the ACA Medicaid Expansion: Childless Adults (138% FPL)

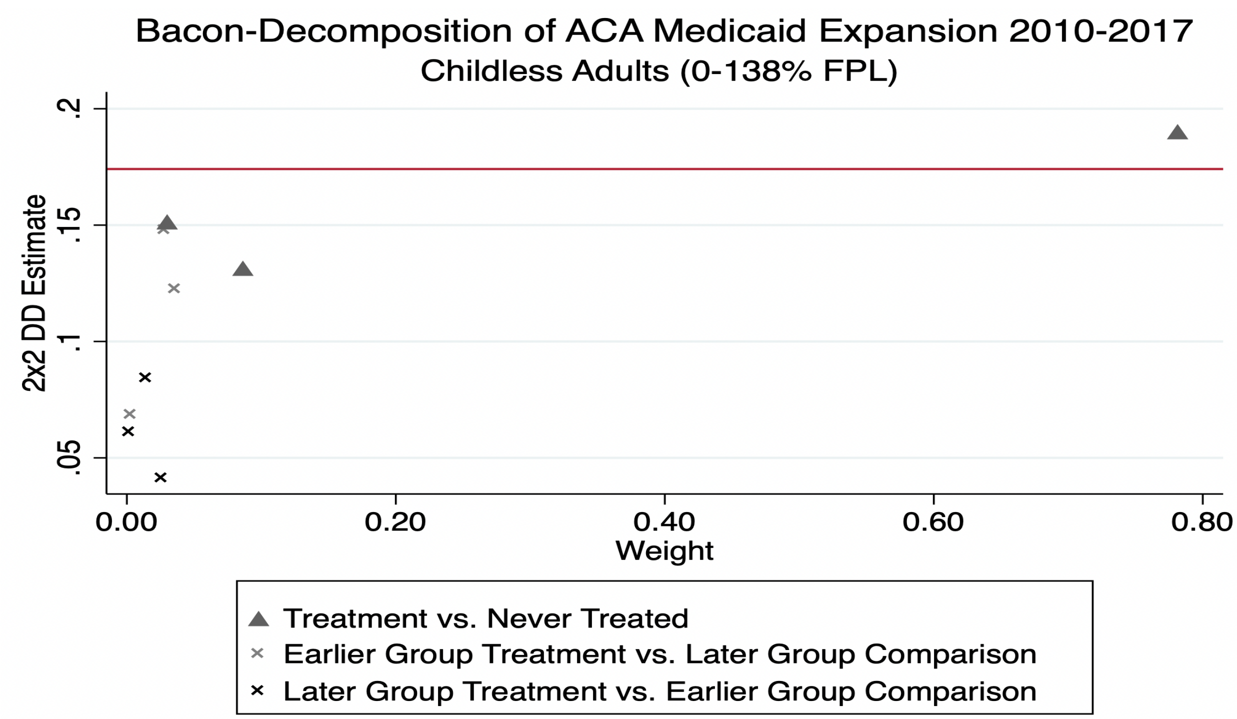
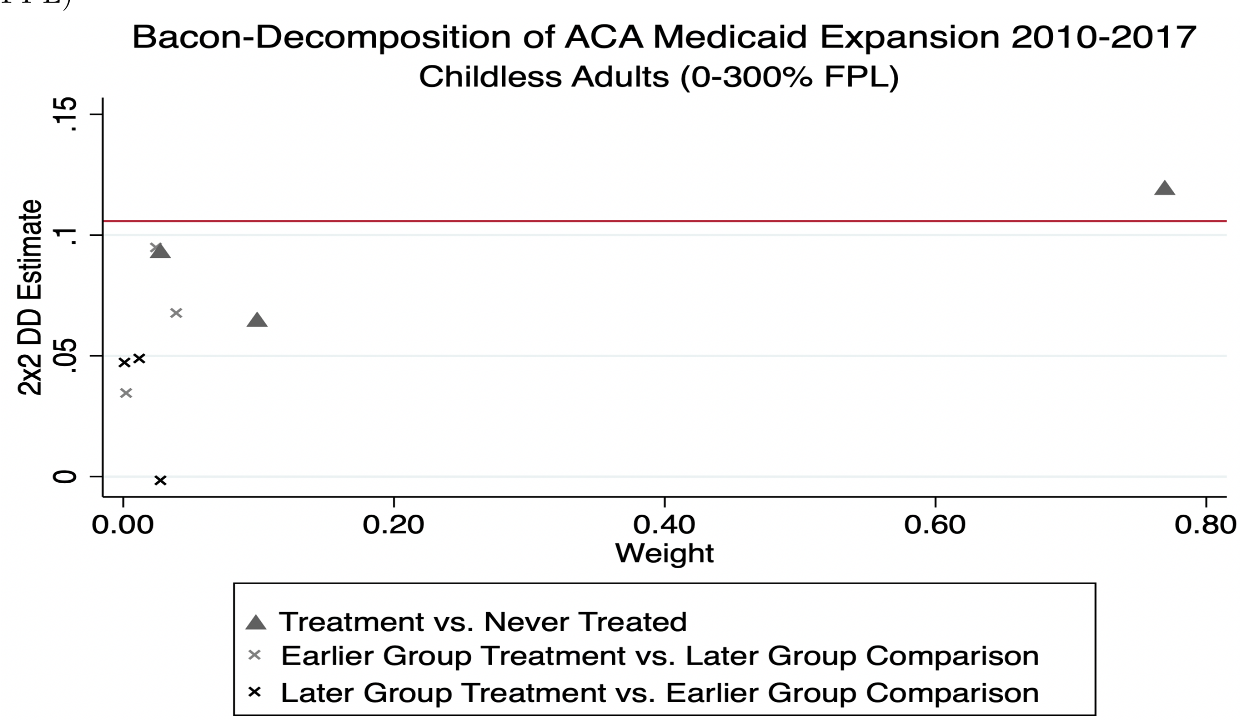


Figure B4: Bacon Decomposition of the ACA Medicaid Expansion: Childless Adults (300% FPL)



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

Table B2: Bacon-Decomposition of the ACA Expansion on Medicaid Coverage for Childless Adults (300% FPL)

DD Comparison	Weight	Average DD Estimate
Earlier T vs. Later C	0.065	0.077
Later T vs. Earlier C	0.040	0.014
T vs. Never treated	0.896	0.112

Treatment=T; Comparison=C