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

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Abstract

What is the likelihood that the ACA Medicaid expansion impacted certain individuals? Using linear discriminant analysis (LDA), I estimate how characteristics relating to race/ethnicity and socioeconomic status 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 were more likely than non-workers to be compliers. This result is more prominent for Black individuals compared to other racial/ethnic groups. This paper not only serves to identify the types of individuals who were directly affected by the expansion, but it also introduces a new approach that combines complier analysis with techniques from machine learning.

Keywords: Medicaid, ACA, Compliers, Linear discriminant analysis

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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). Key provisions of the Affordable Care Act (ACA), including Medicaid expansion, subsidized Marketplace coverage, and the individual mandate were created for the purpose reducing disparities in health coverage that were prevalent across race/ethnicity and socioeconomic status and documented prior to establishment of the ACA (Courtemanche et al., 2016; Courtemanche et al., 2017; Courtemanche et al., 2019; Lee and Porell, 2020). 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] While these studies are helpful in measuring the heterogeneous impacts of the ACA expansion for various populations, they are not informative of who is more likely to be a complier, those induced by the expansion to enroll into Medicaid. Instead, they all relied on difference-in-differences (DID) strategies and stratified the model across various population demographics. However, the characteristics of the compliers cannot be identified through these strategies alone.

This paper introduces a new approach that allows researchers and policymakers to assess the impacts of the ACA Medicaid expansion for the compliers. I combine techniques in econometrics and machine learning to identify which types of individuals, measured on a set of observables, were the 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 that indicate gender, race/ethnicity, education, work status, income, and other individual characteristics. Additionally, I estimate the probabilities of the always takers, those who already enrolled in Medicaid prior to the expansion, and the never takers, those who never enrolled even if a state elected to expand Medicaid.

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

Few studies have integrated complier analysis into the context of policy evaluations for health insurance programs. Ko et al. (2020) estimated the complier characteristics of Supplemental Security Income (SSI) recipients under the New York State Medicaid program. In addition to identifying the characteristics of the compliers, Kowalski (2016) estimates the local average treatment effect (LATE) that derives the average treatment effect of insurance on emergency room utilization for the compliers under the Oregon Health Insurance Experiment. Lastly, Abrigo et al. (2021) estimates the LATE or the impact of expanding health insurance for elderly citizens in the Philippines on out-of-pocket expenditures and health care utilization for the compliers. None of these studies, however, have attempted to estimate which characteristics lead to the likelihood that an individual is a complier. This paper advances the literature by being the first to adopt machine learning techniques that uses individual characteristics such as race/ethnicity, education, work status and income to estimate the probability of being a complier. Moreover, this is the only study to model complier analysis with linear discriminant analysis in any application. Furthermore, this is the first paper to identify the characteristics of the compliers from the 2014 ACA Medicaid expansion.

From a policy perspective, it is important to consider how characteristics such as race/ethnicity, education, income and work status can impact the behavior of low-income individuals in seeking publicly subsidized health coverage. 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 to be limited. This left 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 majority of the coverage gap, however, disproportionately falls on Black childless adults who reside in these states (Artiga et al., 2016). This is largely a product of two factors. First, out of the top 13 states (including DC) that account for 48% of the Black population only 4 states have elected to expand Medicaid in 2014 (Buettgens and Kenney, 2016).[2] Second, Black individuals have historically relied heavily on Medicaid as a continuous source of health coverage as the poverty rate for this group is almost three times higher than the poverty rate observed for White individuals (DeNavas-Walt et al., 2013).

Identifying the compliers is valuable for policymakers as it not only identifies the types of individuals that were impacted by the expansion, but it may also serve to motivate further

[2] 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).

efforts in addressing the coverage gap that is disproportionately borne by race and ethnicity. Additionally, efforts on expanding Medicaid in the remaining 12 states have been challenged on the premise that Medicaid is a safety net program for those who are "undeserving" of assistance. 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 (Applebaum, 2001; Gans, 1995; Moffitt, 2015). However, approximately 60% of non-elderly, and non-disabled adults on Medicaid already work part-time or full-time (Garfield et al., 2017). Nevertheless, some states have implemented work requirements under Section 1115 waivers that set a minimum amount of hours a recipient must work to qualify and maintain continuous coverage in Medicaid (Musumeci et al., 2018).[3] 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). Factoring in high incidence of job loss during the COVID-19 pandemic, especially among minorities (Falk, 2020), the implementation of these waivers could create a scenario where many Americans are without health coverage. Therefore, the techniques in this study can assess whether the characteristics that result in the highest approximation of the compliers are used to define the "undeserving poor".

My identification strategy requires the use of several estimation techniques in tandem with one another. 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 found 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).[4] Next, I compute the average characteristics of the compliers, always takers and never takers using the methods outlined in Kowalski (2016). The compliers in this natural experiment were disproportionately made up of Black recipients, and those in the middle of

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

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

the distributions for work and education. The always takers and never takers were 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, I employ linear discriminant analysis (LDA) to estimate the probabilities of the compliers, never takers and always takers, conditional on a set of observables. Moving along the distributions for work and education, I observed negative and positive gradients in the probability of being an always taker and never taker, respectively. This suggests that those in the top and bottom of the distributions for education and work were the least likely to be induced by the expansion to enroll into Medicaid, given either their eligibility for preexisting Medicaid programs or for employer sponsored health insurance (ESI), respectively. Across multiple specifications, the probability of being a complier was highest for part-time and full-time workers and those in the middle of the distribution for education. Evaluating by race/ethnicity, Blacks were the most likely group to be compliers and were mainly part-time and full-time workers from the middle of the distribution for education. This implies that compared to other races, there are underlying factors that are prevalent amongst low-income Black childless adults and inducing them to seek Medicaid coverage.[5] However, as the majority of the Black population resides in non-expansion states, this leaves them with limited options in accessing affordable health coverage. Furthermore, I find that the characteristics that define the compliers are not consistent with those that define the "undeserving poor". This invalidates the stigma that is based on prejudice views against race/ethnicity and labels Medicaid recipients as "undeserving".[6]

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 under LDA. Finally, Section 6 discusses the findings and concludes.

[5]Evidence that supports this can be found in Andersen et al. (2007). In their model, they argue that race/ethnicity serves as both an predisposing and enabling characteristic at the individual level and influences the use of medical care.

[6]See Dyck and Hussey, 2008; Gilens (2009) and Rigby et al. (2009) for studies that evaluate the relationship between race/ethnicity and welfare support.

2 Background

The 2010 Affordable Care Act (ACA) provided the most significant regulatory changes in the U.S. healthcare system since the introduction of Medicare and Medicaid in 1965. A significant component of the ACA was the expansion of Medicaid to all individuals with incomes below 138% of the federal poverty line (FPL).[7] Originally, the 2010 ACA mandated a nationwide expansion of Medicaid in all states that was set to begin in 2014. However, in 2012, the Supreme Court ruled that states' can voluntarily elect to participate in the expansion instead of being subjected to the mandate. On January 1st, 2014, twenty five states (including DC) adopted the Medicaid expansion with seven additional states adopting between 2014 and 2017. 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.[8] This in turn created a coverage gap for individuals whose income is less than 100% of the FPL and residing in states that did not expand Medicaid.

The ACA redefined how financial eligibility was determined in Medicaid for non-disabled groups with the introduction of 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 equivalent to 5% of the FPL. Other non-income based features of the ACA improved eligibility determination for Medicaid. This included reductions 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.[9] Mean eligibility threshold rates for children were very generous

[7] 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.

[8] 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).

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

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.[10] 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.[11] Figure A2 of the appendix summarizes the changes in the mean Medicaid eligibility thresholds by state between 2013-2014.

3 Data

3.1 American Community Survey

I utilize American Community Survey (ACS) as the main data source for conducting 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 year, representing over 92% of the population in the U.S. 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 prior to the ACA and four years after the ACA was implemented. The ACS identifies all 50 states (including DC) along with 2300 localities or Public Use Microdata Areas (PUMAs). However, I am unable to utilize data at the PUMA-level prior to 2012 as the PUMA boundaries were redrawn after 2011 using the Decennial Census. Therefore, I conduct my analysis at the individual-state level.

The ACS included 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 (e.g. food stamps and housing subsidies), capital gains or losses, and tax credits. The poverty lines are calculated based on family size and number of related children under 18 years old. These thresholds vary across years and are directly from

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

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

the Current Population Survey (CPS).[12] 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 utilized 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, a limitation of the ACS is that it measures Medicaid status by asking if a respondent received "Medicaid, Medical Assistance, or any type of government-assistance plan for those with low incomes or a disability". This potentially serves as a caveat in my study as respondents may misreport private coverage as public coverage and vice versa.[13]

The Supreme Court's 2012 ruling on Medicaid expansion created a quasi-experimental setting that allowed me to assign states into treatment and control groups based on their decision and timing to expand Medicaid. States were 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 were taken directly from the Kaiser Family Foundation (KFF). I excluded states that fully expanded Medicaid prior to 2014 (DC and VT) due to eligibility thresholds for these states being higher than 138% of the FPL. Additionally, I excluded Wisconsin from my sample as they did not participate in expansion, but increased eligibility for childless adults to 100% of the FPL in 2014.[14]

I restricted my sample to individuals that met the following criteria: aged between 26 and 64, childless, and non-disabled. I imposed these restrictions to control for alternative pathways into Medicaid that disregard state by year income eligibility thresholds. Individuals aged 65 and over qualify for Medicare. The ACA allowed individuals under 26 years

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

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

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

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 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. However, 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 was used to determine eligibility into 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 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 incomes 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 addressed these concerns 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

Table 1 reports the summary statistics of the individual demographics in 138% FPL sample by states' expansion status. In expansion states, the before and after periods were set based on when each state expanded Medicaid, while in non-expansion states, the before and after periods were set in 2010-2013 and 2014-2017, respectively. Overall, there were no notable differences across time periods in both groups. However, comparing by states' expansion status, non-expansion states had a higher Black population, a lower NHAAPI popluation, and a greater portion of those who were 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 were 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 between 2 to 3 percentage points. This illustrates a higher concentration of Black childless adults when restricting the sample to those in higher poverty. Next, I observed 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 in the 138% FPL sample. The mean rate of Medicaid coverage increased before and after the expansion by roughly 20% in expansion states and by 3% in non-expansion states. Changes by race/ethnicity in expansion states differ slightly with increases in Medicaid coverage of 22% for Whites, 19% for Blacks, 19% for Hispanics and 17% 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.

I report the time series of health coverage variables for the 300% FPL sample in table A2 of the appendix. Compared to table 2, average gains in Medicaid coverage have narrowed to approximately 13% in expansion states and 2%, 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 uninsured rate were smaller that what was reported in table 2 at 16% and 9% 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).[15] 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 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 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. Using a difference-in-differences (DID) model with staggered treatment, I estimate $p_1 - p_0$ which corresponds to the effects of the ACA Medicaid expansion on Medicaid coverage. I estimate the following regression:

$$D_{ist} = \beta_0 + \beta_1 Z_{st} + \beta_2 X_{ist} + \gamma_t + \phi_s + \epsilon_{ist} \tag{2}$$

[15] 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.

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 binary indicator that equals to 1 if individual i resided in a state s that opted to expand Medicaid at time t, and 0 otherwise. While most states expanded Medicaid on January 1st, 2014, 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 prior or on July 1st, 2014.[16]

Theoretically, all individuals whose incomes are less than 138% should be eligible for Medicaid if they resided 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 affects 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 individual enroll into 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 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 demographic characteristics X_{iast} such as age group, 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. All standard errors are clustered 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.

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 assess the changes in health insurance outcomes while controlling for fixed differences across states and national trends over time.

[16] There are 6 states: AK, IN, LA, MT, NH and PA that expanded Medicaid after July 1st, 2014. States defined to have expanded in 2015 are PA (Expanded on January 1, 2015) , IN (February 1, 2015), and NH (on August 15, 2014). States AK (September 1, 2015) and MT (January 1, 2016), and LA (July 1, 2016) were classified to have expanded in 2016.

The specification for the event study is as follows:

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

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 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. This is done to avoid multicollinearity in the relative time indicators. I "trimmed" the data by omitting values for $y < -4$ since I observed $y < -4$ only for late expansion states.[17] This address the 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 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 (3) using a linear probability model with ACS survey weights and cluster the standard errors at the state level.

4.3 Complier Characteristics

In this section, I employ complier analysis to estimate the characteristics of individuals who became eligible under the expansion and enrolled into Medicaid. The identification of these individuals can assist policymakers in understanding how the ACA expansion impacted Medicaid enrollment patterns across various population demographics.

Following the methodology from Angrist et al. (1996), I divide the population into three classes: always takers, never takers, and compliers.[18] Figure 1 summarizes the take-up of treatment based on an individual's propensity scores discussed in section 4.1. First, individuals with $0 \leq U < p_0$ are classified as always takers and will always seek treatment. Within the context of the model, always takers will enroll into Medicaid even if they resided in a state that did not elect to participate in the ACA Medicaid expansion. These also represent individuals that qualified for Medicaid via Supplemental Security Income (SSI)

[17] 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.

[18] Angrist et al. (1996) define a 4th class: defiers who receive treatment if assigned to the control and do not receive treatment if assigned to treatment. Consistent the literature, I exclude the defiers from the analysis under the assumption of monotonicity.

benefits or through state Medicaid programs that existed before the enactment of the 2014 ACA Medicaid expansion.[19] In the data, if $Z = 0$ and $D = 1$, then the individual is an always taker (note that this is a necessary, but not a sufficient condition). Second, compliers are individuals with $p_0 \leq U < p_1$ and will enroll into Medicaid only if they reside in states that participated in the expansion at time t. Alternatively, these individuals will not enroll in Medicaid if they resided in a state that did not participate in the expansion at time t. Therefore, if $Z = D$, then the individual is a complier. This class represents the population that became eligible for Medicaid under the new state-level income thresholds introduced in year t and enrolled into Medicaid. 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 enrollment. Lastly, individuals with $p_1 \leq U \leq 1$ are never takers and will never seek treatment even if they are assigned to the treatment group. In other words, this class represents individuals that will never enroll into Medicaid even when residing in a state that has participated in the expansion at time t. Therefore, individuals with $Z = 1$ and $D = 0$ are classified as never takers.

Unlike the always takers and the never takers, individuals in the compliers group cannot be separately identified in the data. Individuals with Z=1 and D=1 designates the intervention treated group which is comprised of always takers and treated compliers. Similarly, individuals with Z=0 and D=0 designates the baseline untreated group which is comprised of never takers and untreated compliers. I adopted methods from previous studies to estimate the characteristics of the compliers group (Abadie, 2002; Abadie, 2003; Imbens and Rubin, 1997; Katz et al., 2001; Kowalski, 2016; Abrigo et al., 2021). My identification strategy involves employing methods from Kowalski (2016) and Abrigo et al. (2021) that solves for the weighted average of the characteristics of both the treated and untreated compliers. Formally, this can be specified as solving for $E[X \mid D = d, p_0 \leq U < p_1]$ for $d \in \{0, 1\}$. I

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

solve for average characteristics of the untreated compliers by calculating:

$$\begin{aligned}
\mu_x(0) &= E(X \mid D=0, p_0 \le U < p_1) = E(X \mid Z=0, p_0 \le U < p_1) \\
&= \frac{1}{p_C}\left[E(X \mid p_0 \le U \le 1)\, p_{NTUC} - E(X \mid p_1 \le U \le 1)\, p_{NT}\right] \\
&= \frac{1}{(p_1 - p_0)}\left[E(X \mid p_0 \le U \le 1)\,(1-p_0) - E(X \mid p_1 \le U \le 1)\,(1-p_1)\right] \\
&= \frac{1}{(p_1 - p_0)}\left[E(X \mid Z=0, p_0 \le U \le 1)\,(1-p_0) - E(X \mid Z=1, p_1 \le U \le 1)\,(1-p_1)\right] \\
&= \frac{1}{(p_1 - p_0)}\left[E(X \mid Z=0, D=0)\,(1-p_0) - E(X \mid Z=1, D=0)\,(1-p_1)\right]
\end{aligned} \tag{4}$$

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

Similarly, I calculate the average characteristics for the treated compliers by

$$\begin{aligned}
\mu_x(1) &= E(X \mid D=1, p_0 \le U < p_1) = E(X \mid Z=1, p_0 \le U < p_1) \\
&= \frac{1}{p_C}\left[E(X \mid 0 \le U < p_1)\, p_{ATTC} - E(X \mid 0 \le U < p_0)\, p_{AT}\right] \\
&= \frac{1}{(p_1 - p_0)}\left[E(X \mid 0 \le U < p_1)\, p_1 - E(X \mid 0 \le U < p_0)\, p_0\right] \\
&= \frac{1}{(p_1 - p_0)}\left[E(X \mid Z=1, 0 \le U < p_1)\, p_1 - E(X \mid Z=0, 0 \le U < p_0)\, p_0\right] \\
&= \frac{1}{(p_1 - p_0)}\left[E(X \mid Z=1, D=1)\, p_1 - E(X \mid Z=0, D=1)\, p_0\right]
\end{aligned} \tag{5}$$

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

Next, I take the weighted sum of the averages of the untreated and treated compliers to derive the average of the observed characteristics for the compliers group.

$$E(X \mid C) = w\, \mu_x(0) + (1-w)\, \mu_x(1) \tag{6}$$

Here the weight w can be chosen optimally by setting

$$w* = \frac{V(\widehat{\mu_x(1)}) - C(\widehat{\mu_x(0)}, \widehat{\mu_x(1)})}{V(\widehat{\mu_x(0)}) + V(\widehat{\mu_x(1)}) - 2C(\widehat{\mu_x(0)}, \widehat{\mu_x(1)})}$$

which minimizes the variance of the estimates.

Following Kowalski (2016) and Abrigo et al. (2021), I calculate the conditional expectations directly from the data. I denote X_{ist} as some individual characteristic and estimate the following regression:

$$X_{ist} = \lambda_{NT} + \lambda_{AT}\, 1(AT_{ist}) + \lambda_{AT+TC}\, 1(ATTC_{ist}) + \lambda_{NT+UC}\, 1(NTUC_{ist}) + \gamma_t + \phi_s + u_{ist} \quad (7)$$

where NT identifies the never takers, AT identifies the always takers, NTUC identifies the composite of never takers and untreated compliers, and ATTC identifies the composite of always takers and treated compliers. The term λ_{NT} is 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. The coefficients from the regression provides conditional expectations needed to solve for equations (4) and (5). Finally, I am able to solve for the weighted average of the compliers that could not be separately identified in the data.

4.4 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 the classes have equal covariance matrices. In this context, each class to corresponds to either an always taker, complier or 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 the complier analysis outlined in section 4.3.

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 a complier

C using equation (8).

$$P(C \mid x) = \frac{P(x \mid C)\,(p_1 - p_0)}{P(x \mid AT)\,p_0 + P(x \mid C)\,(p_1 - p_0) + P(x \mid NT)\,(1 - p_1)} \tag{8}$$

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. Each density is multiplied by the propensity scores derived from equation (2). I modify equation (8) to approximate the posterior probabilities of being either an always taker or a never taker. To conduct inference, I report the means and 95% confidence intervals for the posterior probabilities from 1000 bootstrapped re-samples.

I summarize the methodology of approximating the posterior probability of compliers, always takers and never takers in five steps. First, I run the regression in equation (2) 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 individual characteristic using equation (7). Third, I utilize the estimates from the previous steps alongside equations (4) and (5) to calculate the conditional expectations of the compliers using equation (6). Fourth, I calculate the class conditional density functions for each set of individual characteristics using the class conditional expectations derived in equations (6) and (7). Finally, I utilize the density functions, propensity scores and conditional expectations to approximate the posterior probabilities of the compliers, always takers and never takers for each set of individual characteristics in equation 8.

5 Results

5.1 Difference-in-Differences Results

In Table 3, I provide the results from the DID regression in equation 2 on the effects of the ACA Medicaid expansion on health coverage. The 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. The 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 significantly 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 to be targeted from 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 my sample restrictions and longer time periods, the size of my estimates are slightly higher than what is reported in the literature.

I observed 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 were approximately 2.8 to 4.6 percentage points. The coefficients for private insurance and uninsurance sum nearly to the amount reported for Medicaid in both subgroups, showing limited evidence that beneficiaries are dual enrolling into Medicaid and private insurance.[20] 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 result 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 evolved similarly to that in non-expansion states in the absence of the ACA Medicaid expansion. Therefore, I utilize the event-study model outlined in equation 3 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 Table A3 of the appendix. Figures 2 and A3 illustrate the results of the sample groups below 138% FPL and below 300% 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.

[20] 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.

The patterns of the event studies are similar across both low-income sub-samples. In the pre-period, I observed near zero and insignificant effects of the ACA expansion on all health insurance variables for both low-income sub-samples. This shows the parallel trends assumption holds and supports the validity of my baseline estimates. In the post-period, I observed positive and statistically significant changes in Medicaid coverage over time. These increases potentially reflect heightened awareness, individual mandate, reduction 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 2, I observed negative and statistically significant changes in private coverage and uninsurance rates for both low-income sub-samples.

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 derived under equation (7). 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 A8 and A9 of the appendix.[21] Each panel corresponds to a different set of characteristics with the means and 95% confidence intervals calculated using 1000 bootstrapped re-samples. I report these separately for the always takers, compliers, never takers and unconditional mean. 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.

Females were only slightly more likely to be compliers than males. However, in both income sub-samples, the compliers were 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 than the means of the always takers and never takers depending on the income sub-sample. Those

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

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 falls below the means in the 300% FPL sample. The exact opposite occurs for Blacks in both income sub-samples. Both Hispanics and NHAAPIs were 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 are 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 this exercise. First, I identified the compliers were mainly those from the middle of education distribution and work distribution. This can be explained by the positive relationship between education, employment, and income. Those who were uneducated or not working likely acquired Medicaid coverage 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 opted to not seek Medicaid. However, those who worked part-time were unable to qualify for ESI coverage, thereby motivating them to enroll into 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 were 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 suggests that even at higher incomes, Black individuals have a higher need, preference, and demand for Medicaid compared to other racial/ethnic groups

(Andersen et al., 2007). Additionally, I find that NHAAPIs are the least likely to be compliers compared 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 discriminating variables. 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 resamples.

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.

Examining by race/ethnicity, the probability of being a complier is highest for Blacks. Additionally, they are more likely to be always takers and less likely to be never takers compared to other racial/ethnic groups. 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 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 in having the lowest rates of the compliers. This supports previous studies that cited barriers relating to accessibility, financial burden and perceived need as 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 A10 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 A11, the complier means for part-time workers greatly exceeds 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 distribution and work distribution, I run LDA across work status, education and race/ethnicity in figure 7. I select race/ethnicity over gender as the former has exhibited to have wider heterogeneity in the results summarized in figures 5 and 6. 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 over education in explaining the differences in the probability of the compliers.

In figure 8, I estimate the compliers 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 in the bottom of the income distribution 0-50% FPL were 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 are eligible, or faced barriers that prevent them from enrolling.[22]

5.4 Additional LDA Results

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 A14 and A15 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 the 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 into Medicaid. Older adults were likely to have exhausted all options to enroll into 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 A16 and A17 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 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.[23] 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

[22] Previous studies have cited a phenomenon known as the "welcome mat" or "woodwork" effect where recipients who were unaware that they 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 on how this affected childless adults who were eligible programs that offered Medicaid assistance prior to the ACA.

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

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 has negative consequences on 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 A18 and A19 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 a product of crowd-out of private coverage or dual enrollment patterns of both Medicaid and private insurance. However, the results from table 2 suggest that there were 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 crowd-out of private insurance, although additional research is needed to substantiate this claim.

5.5 Robustness Checks

Recently, researchers have been concerned with accurately interpreting the estimates from models with variations in treatment timing. Specially, 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. Therefore, 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 utilize the alternative estimation method proposed in their study. Following their methodology, I calculated 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 A4 and A5 of the appendix. The point estimates across time periods are very similar and 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. Specifically, issues arise when states that already expanded are set as a control to states that later expanded after the initial ACA Medicaid expansion in 2014. This is problematic as that the 2x2 DD estimate is a weighted average of all two-group DD estimators. However, this is likely not a concern in this study 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 A6 and A7 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 is not significantly different from what is reported in the main result.

6 Discussion and Conclusion

This paper introduces a new approach in evaluating who was directly impacted under the ACA Medicaid expansion. This is not only the first paper that combines LDA with complier analysis, but it is also the first to identify the compliers in setting of the ACA expansion. Using national-level data from the ACS, I employed LDA to identify which characteristics for low-income childless adults can predict the probability of the compliers under the ACA expansion.

Consistent across all racial/ethnic groups, the compliers are more likely to be part-time and full-time workers in the middle of the education distribution. Therefore, the characteristics that negatively depict Medicaid recipients as the "undeserving poor" cannot be used to describe the compliers. This is particularly strongest for Black individuals as they were more likely to be compliers compared to all other racial/ethnic groups. Critics of welfare support have associated the unemployed with Black recipients who have been perceived as lazy and "undeserving" of government assistance (Gilens, 2009; Dyck and Hussey, 2008). Contrary to this belief, I find that the compliers are not only more likely to be Black individuals, but they are also mainly part-time and full-time workers drawn from the middle of education distribution. Additionally, I find that the probability of being a never taker are much higher for Hispanic and NHAAPI individuals compared to White individuals. This potentially highlights barriers in accessibility that are intrinsic to race and ethnicity and have not been completely addressed under the ACA Medicaid expansion.[24]

The finding from this paper has important policy implications. States are currently engaging in efforts to waive restrictions against imposing work requirements as a determination for Medicaid eligibility. The implementation of these requirements are motivated by the belief that Medicaid recipients are unmotivated to find work, thus "undeserving" of assistance. However, as many adults experienced income and job loss during the COVID-19 pandemic, both eligibility and enrollment into Medicaid increased, highlighting a greater need for safety net coverage for those previously laid off (Corallo and Moreno, 2022). The implementation of work requirements will therefore result in many Medicaid recipients becoming newly ineligible and exacerbate the coverage gap that is disproportionately borne by racial/ethnic minorities. This is primarily important for Black individuals as they are the most likely racial/ethnic group to be compliers, but heavily reside in non-expansion states. My results show that the characteristics that labeled Medicaid recipients as the "undeserving poor" and motivated the adoption of these work requirements cannot be used to identify the compliers under the ACA Medicaid expansion. Instead, I show that even amongst higher levels of socioeconomic status, there are unobserved factors in race/ethnicity that affect an individual's demand, need and ability to enroll into Medicaid.

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. It is with hope that the techniques in this paper will motivate future work toward identifying the compliers and assessing whether their health care needs are being met.

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[24]An alternative explanation is that these individuals may be hesitant to access Medicaid due to the stigma tied to receiving public-assistance. Further research in this area is warranted.

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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)

Source: ACS 2010-2017

Source: Means were weighted by 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

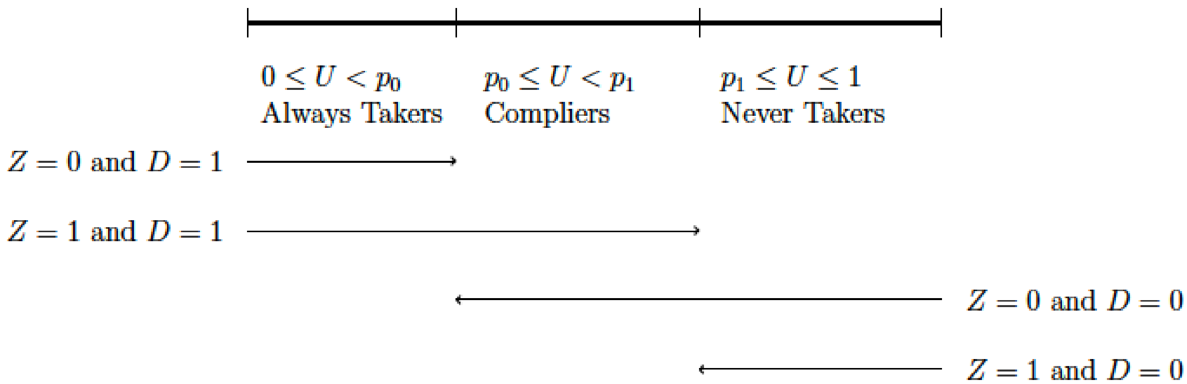
Means were weighted by ACS weights
Standard errors reported in parentheses

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	✓	✓	✓	✓	✓	✓	✓	✓

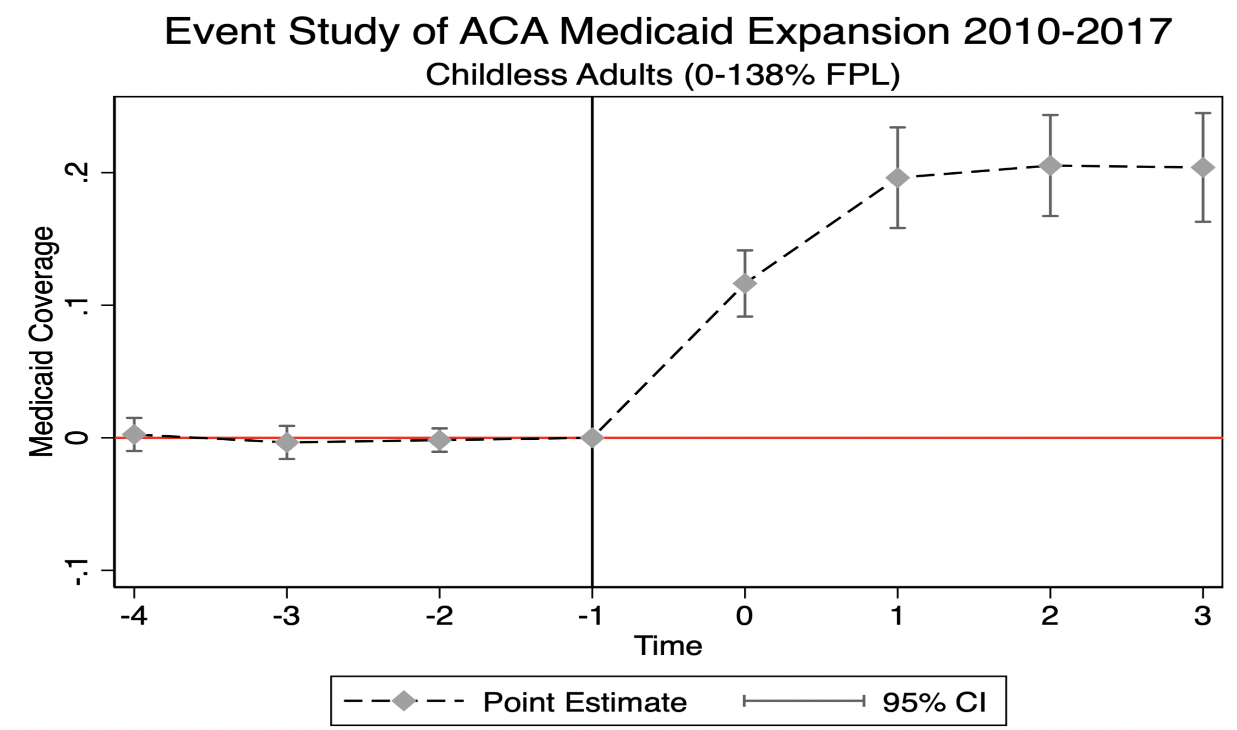
Note: Sample is restricted to non-disabled childless adults aged 26-64. Standard errors clustered at the state-year level are provided in parentheses (*** p<0.01, ** p<0.05, * p<0.10). Each cell reports the results from regressing the main effects of policy variables outlined in equation 2 and several observable characteristics on different types of health insurance indicators across two different income samples. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

Figure 1: Treatment Groups from Complier Analysis



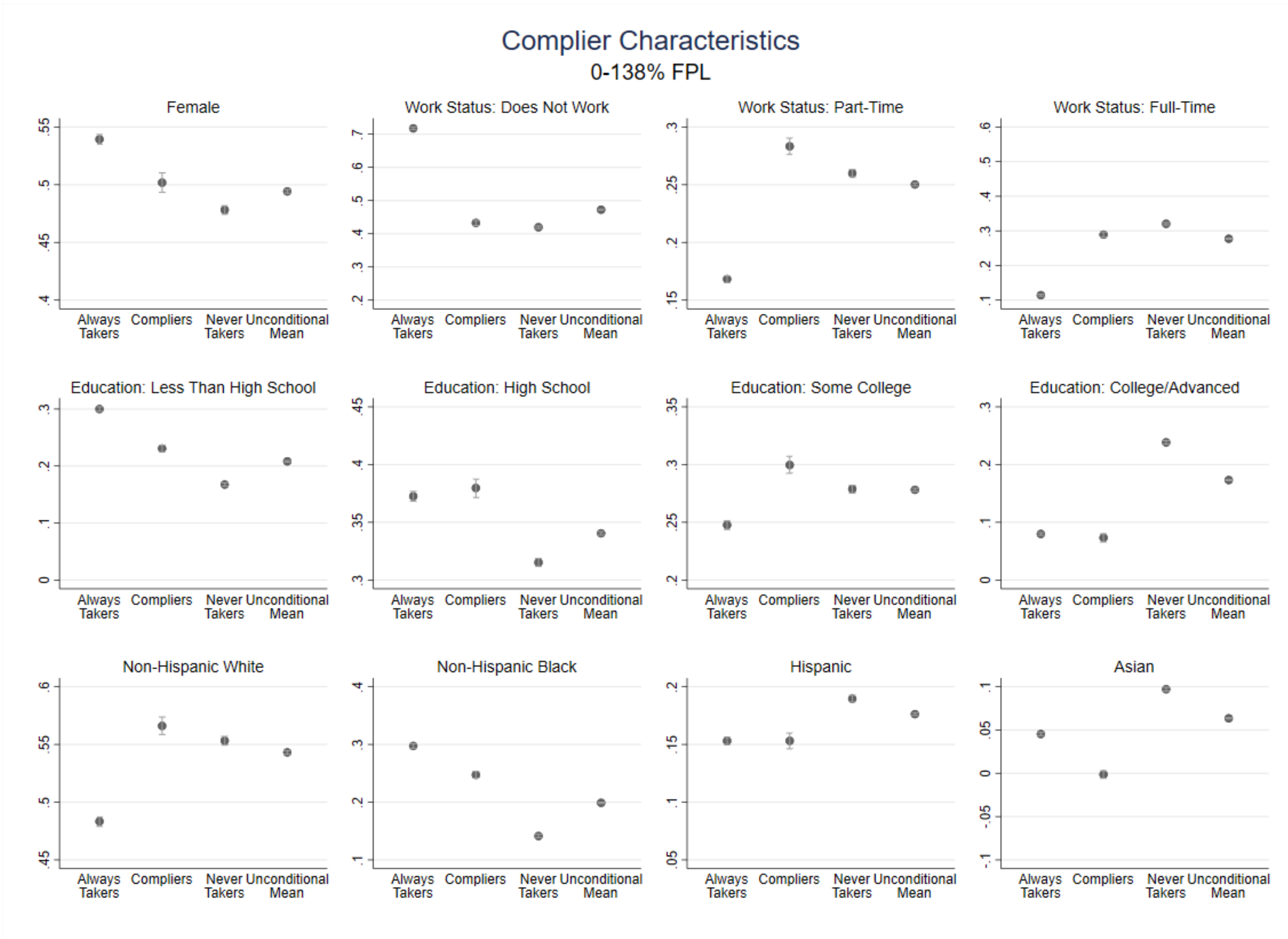
Source: Abrigo et al. (2021)

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



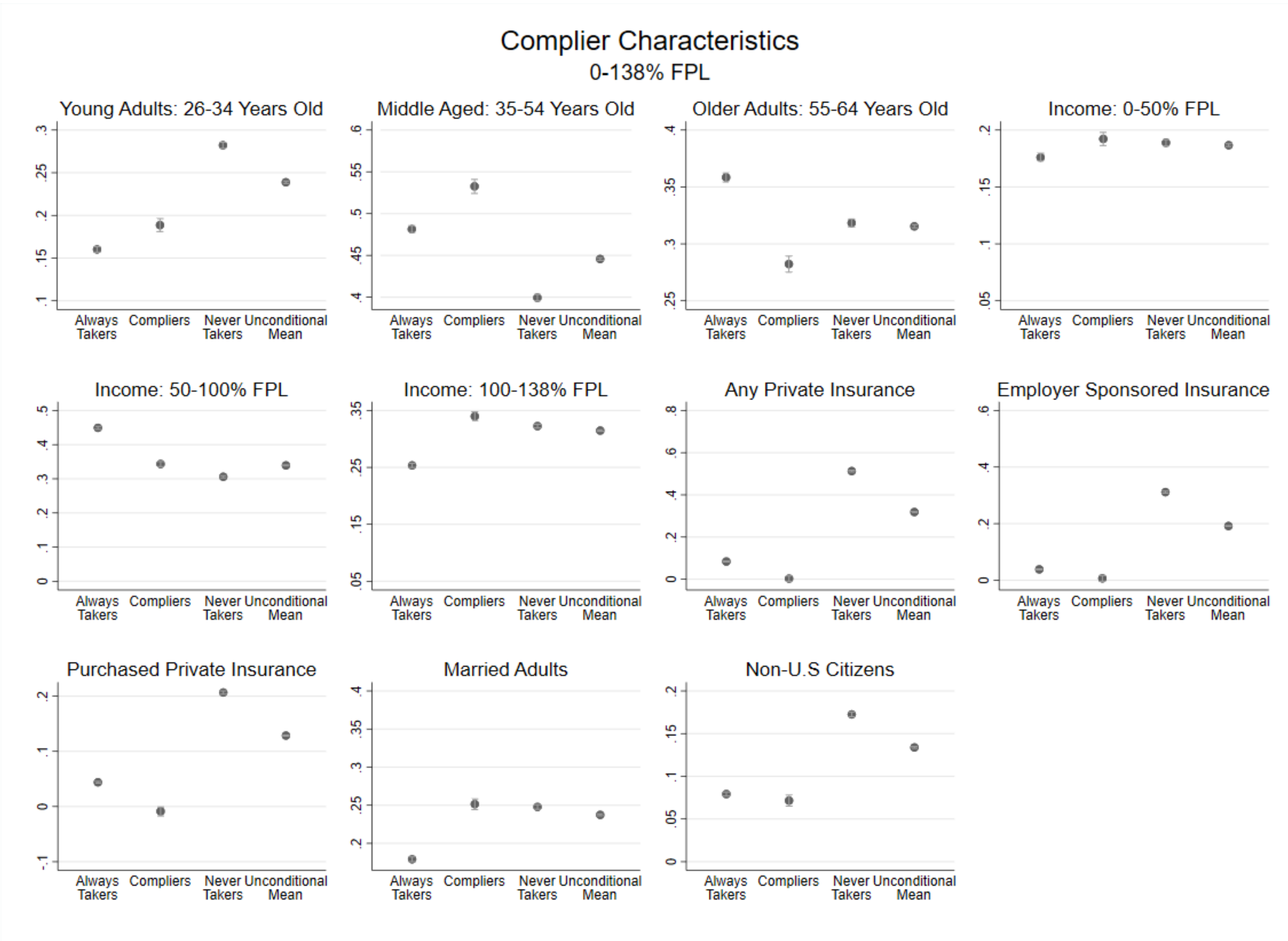
Note: This figure reports the coefficients from estimating equation using techniques outlined in equation 3 with Medicaid coverage as the outcome from the 2010-2017 American Community Survey (ACS). The solid line separates the pre- and post-treatment event study coefficients. The sample is restricted to childless adults age 26-34 with incomes below 138% FPL. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

Figure 3: Observable Characteristics for Always Takers, Compliers and Never Takers: Gender, Work Status, Education, Race, 0-138% FPL



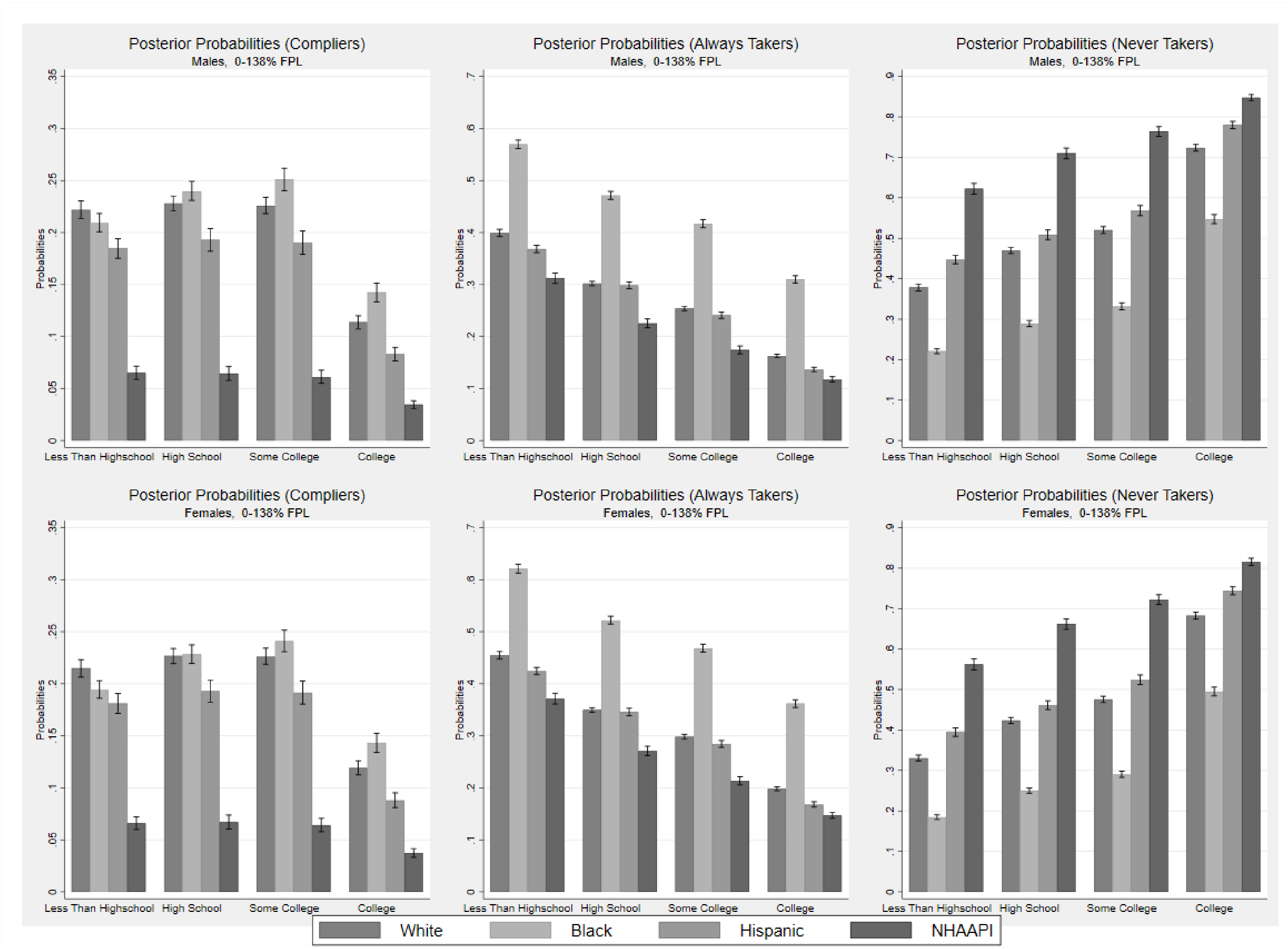
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

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



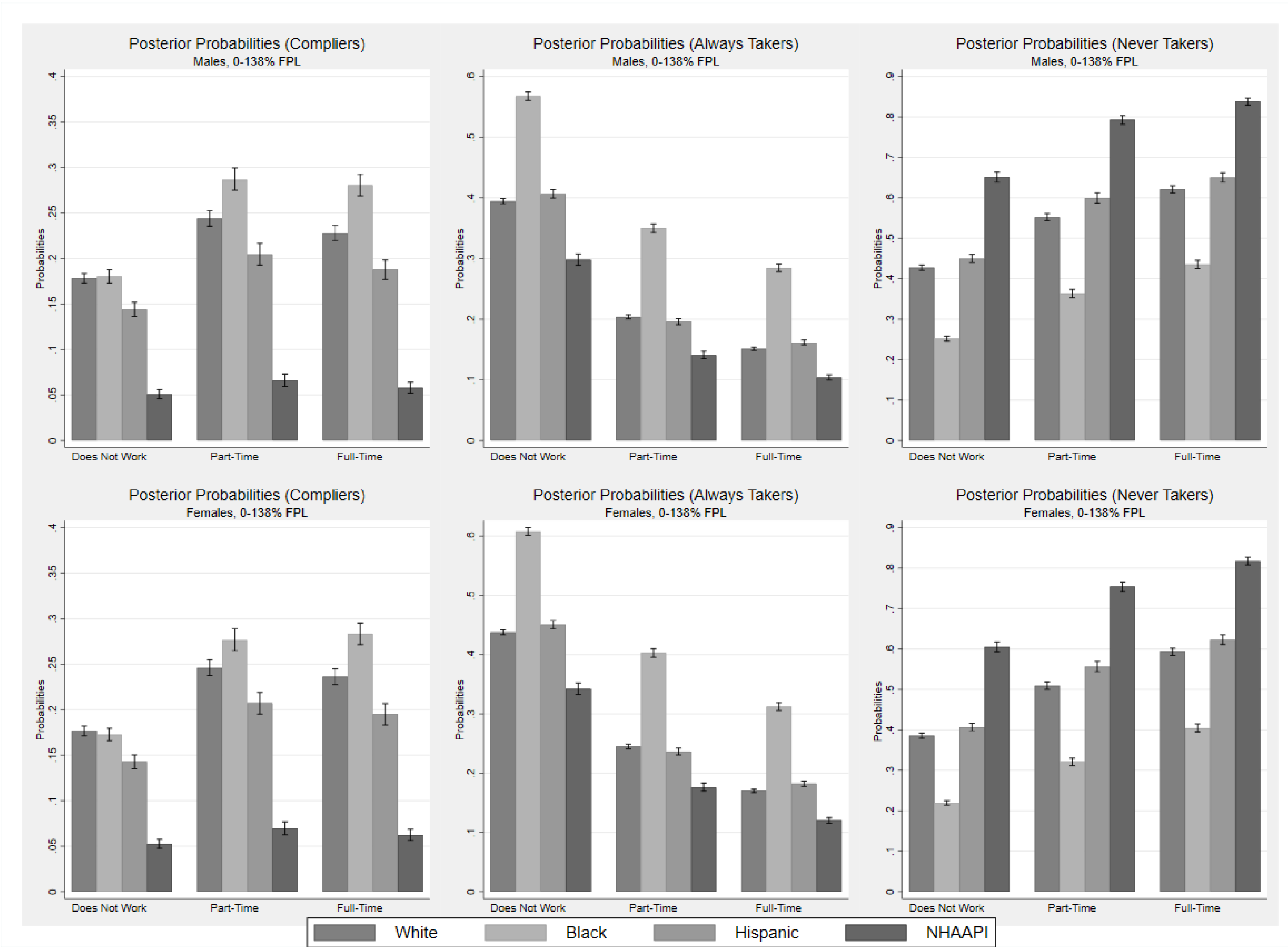
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

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



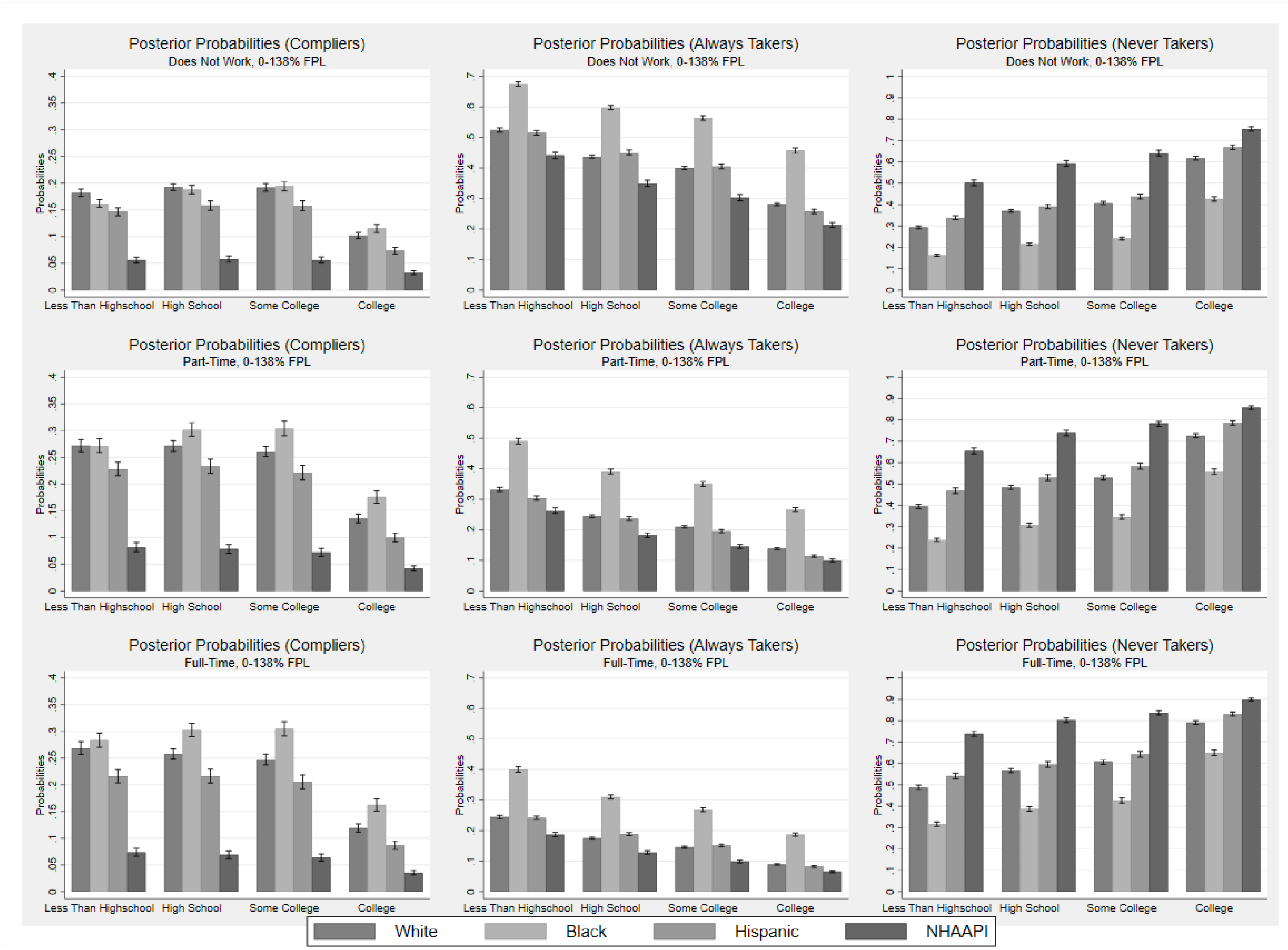
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

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



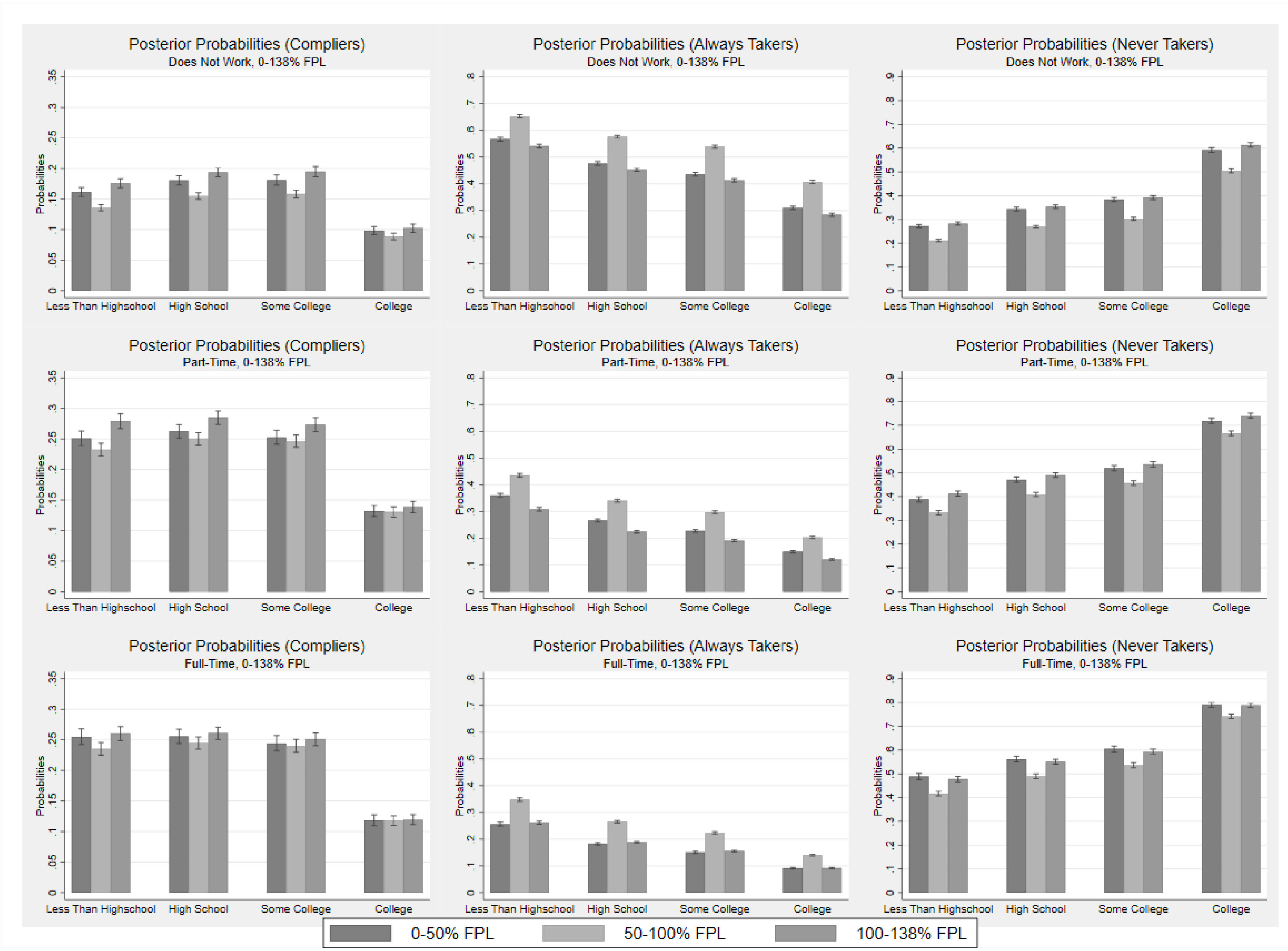
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

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



Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

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



Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

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)

Source: ACS 2010-2017

Source: Means were weighted by 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

Means were weighted by 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	✓	✓	✓	✓	✓	✓

Note: Sample is restricted to non-disabled childless adults aged 26-64. Standard errors clustered at the state-year level 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 3 and several observable characteristics on different types of health insurance indicators across two different income samples. Controls include sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

Table 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

Source: ACS 2010-2017

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

Source: ACS 2010-2017

Table A6: 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

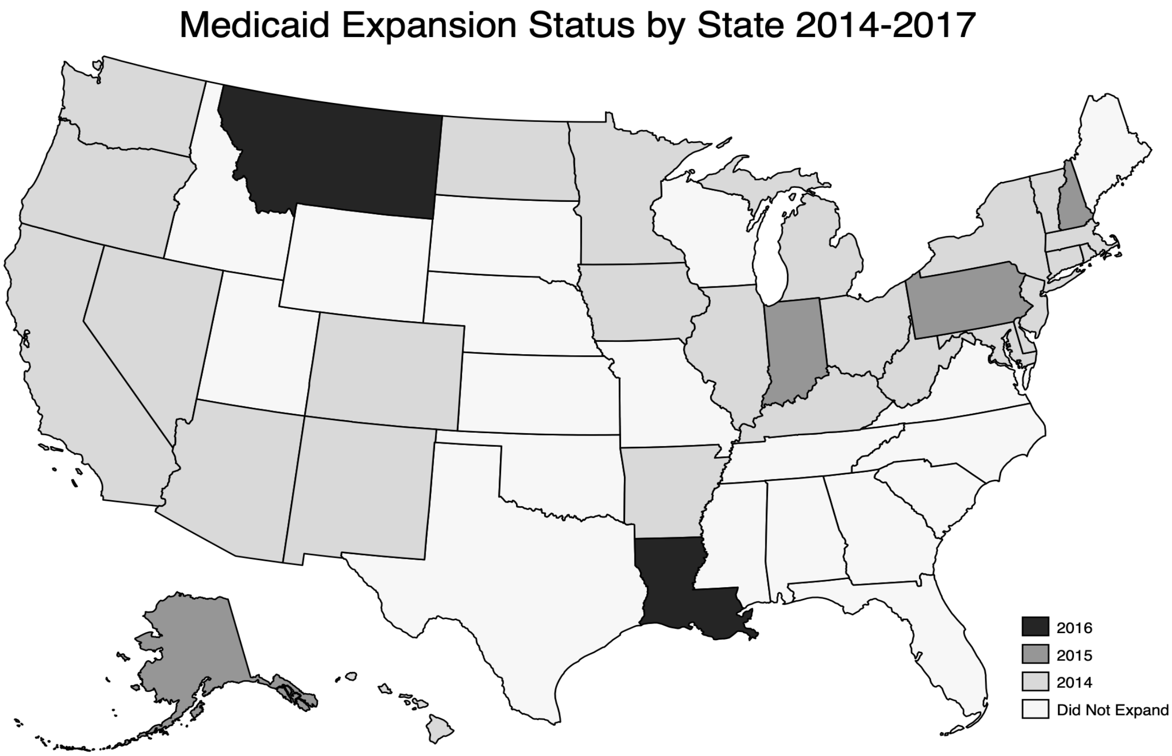
Treatment=T; Comparison=C

Table A7: 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

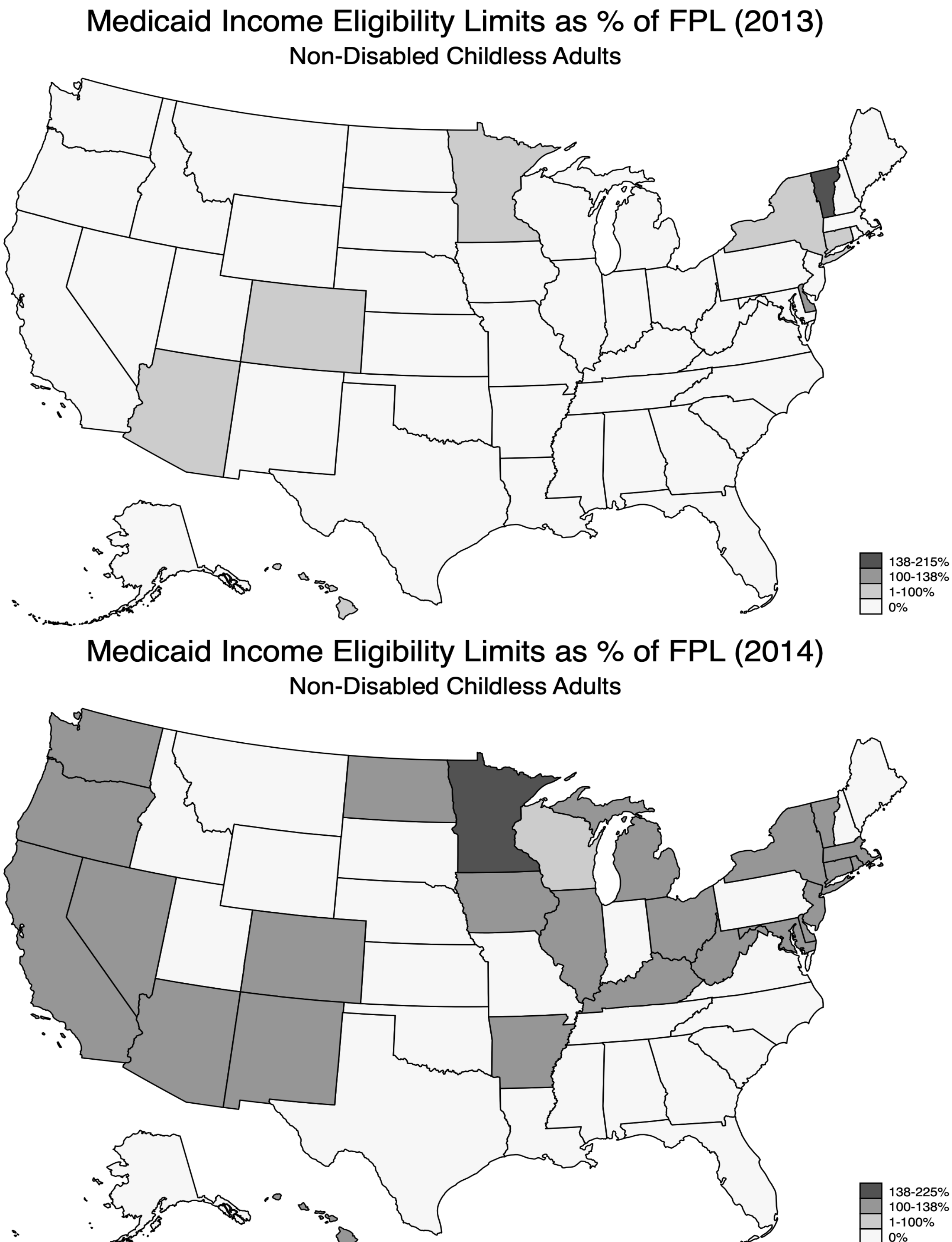
Treatment=T; Comparison=C

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



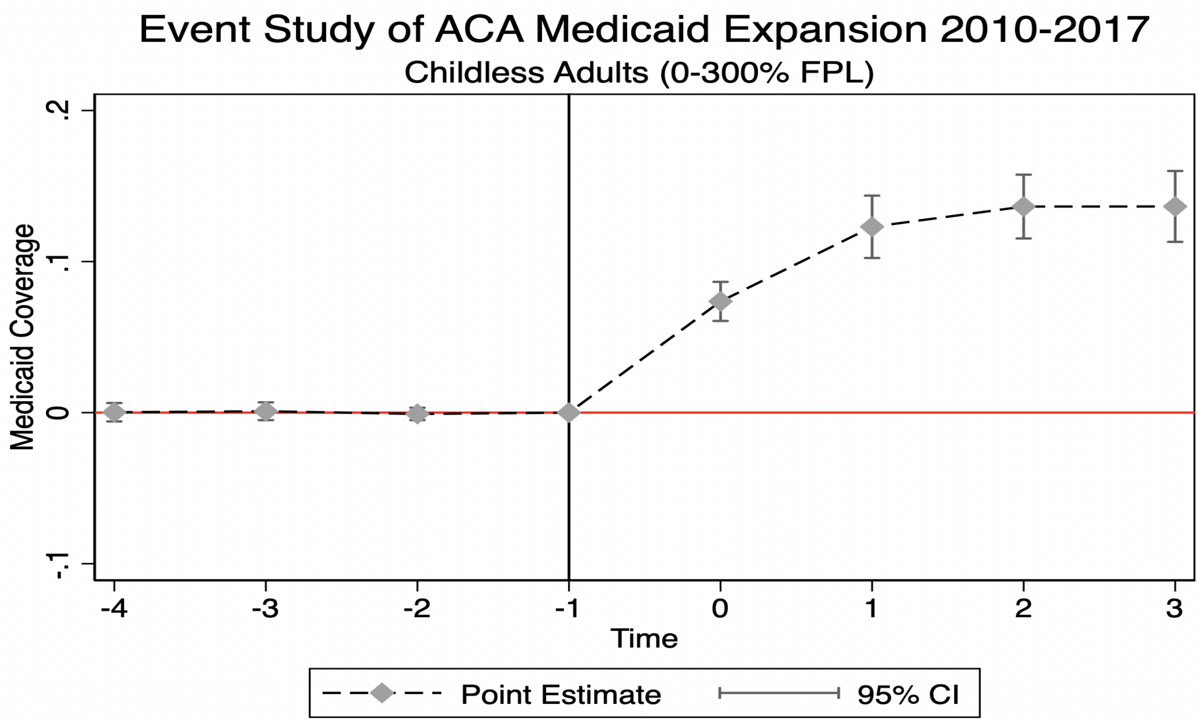
Note: Figure was created by author using information on states' expansion status from the Kaiser Family Foundation (KFF).

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)



Note: This figure reports the coefficients from estimating equation 3 with Medicaid coverage as the outcome from the 2010-2017 American Community Survey (ACS). 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 sex, race, educational attainment, age group, work status, marital status, foreign-born status, and citizenship status. All estimates were weighted using ACS weights.

Figure A4: Event Study (Sun and Abraham, 2020) of the ACA Medicaid Expansion: Childless Adults (0-138% FPL)

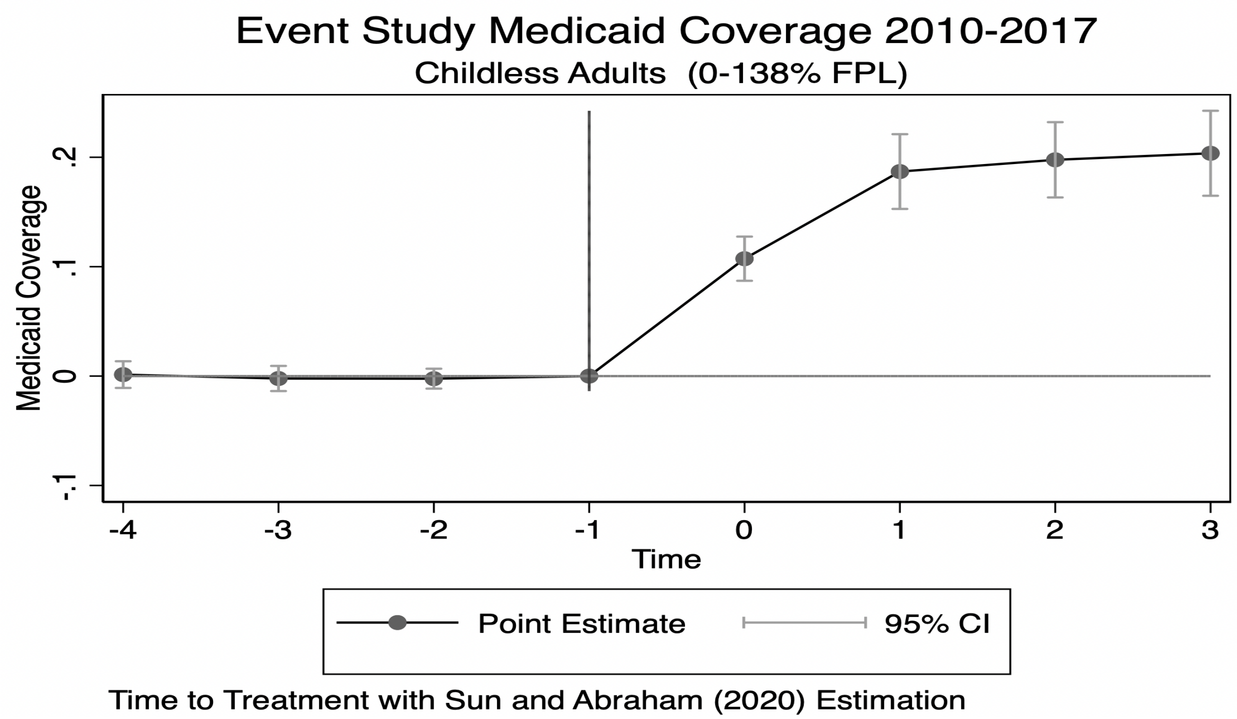
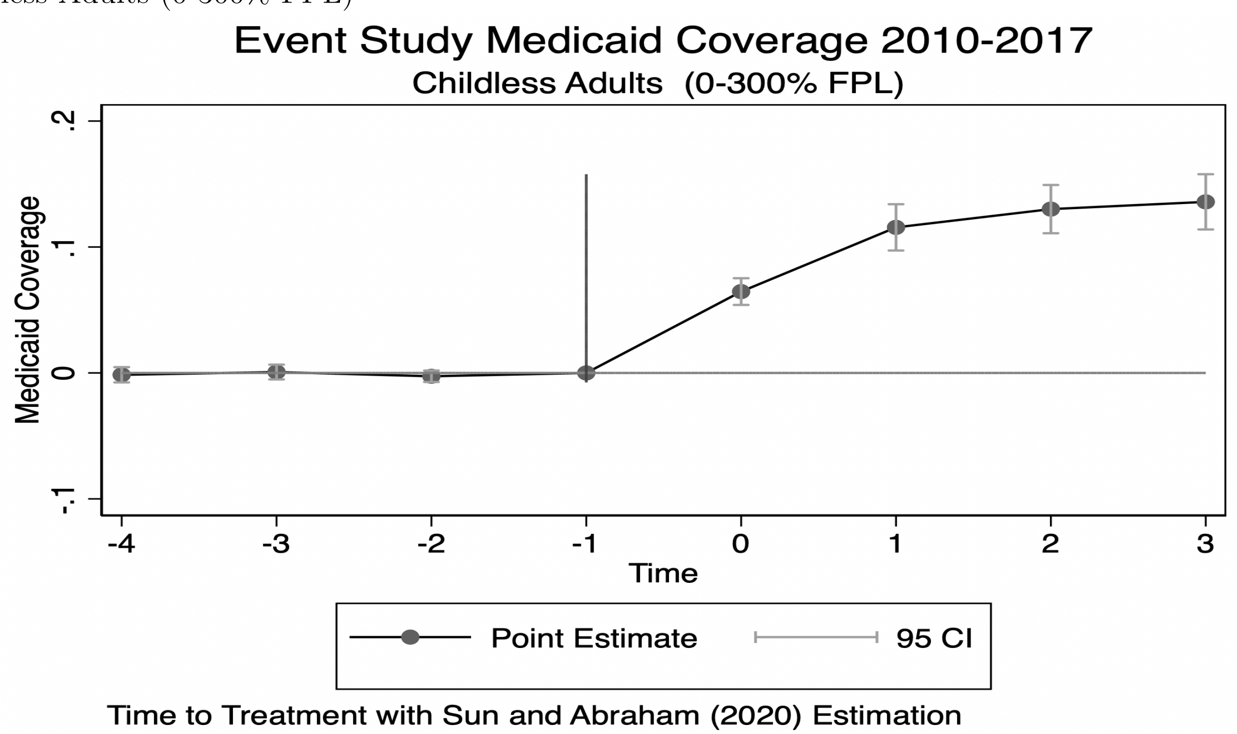


Figure A5: Event Study (Sun and Abraham, 2020) of the ACA Medicaid Expansion: Childless Adults (0-300% FPL)



Note: Each panel reports the coefficients from using an alternative "interaction-weighted" estimator from outlined in Sun and Abraham (2021). See section 5.5 for more details.

Figure A6: Bacon Decomposition of the ACA Medicaid Expansion: Childless Adults (138% FPL)

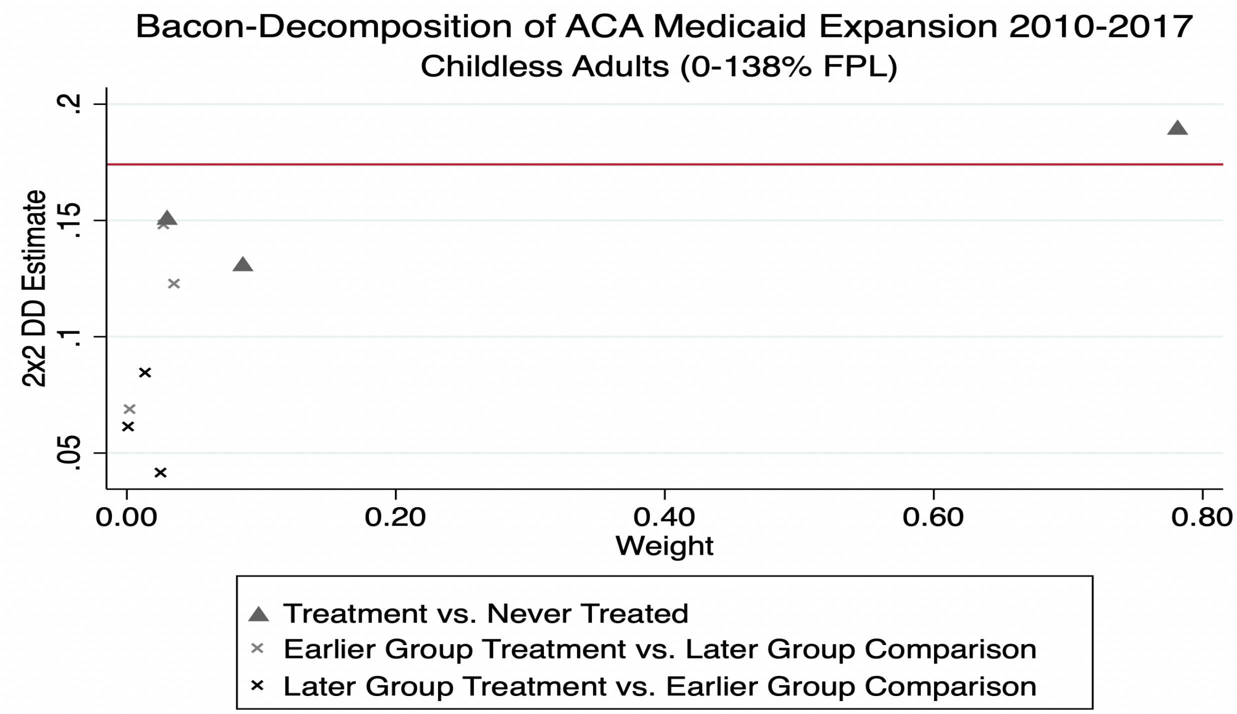
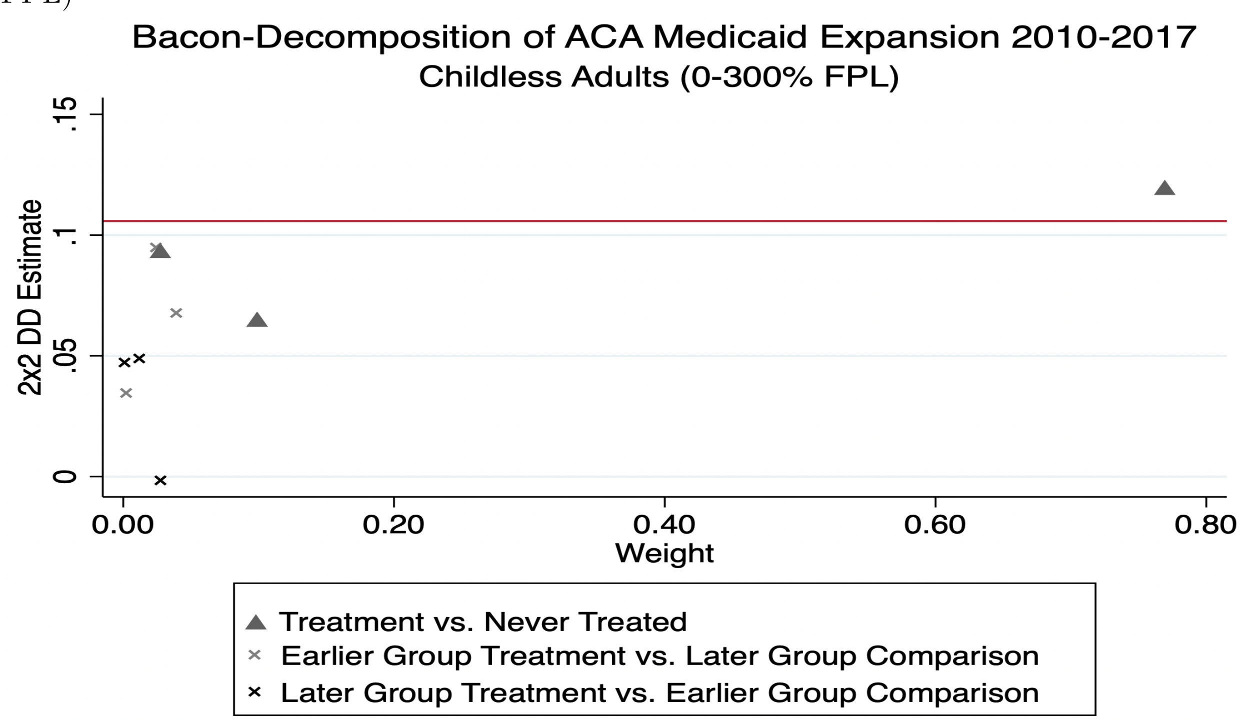
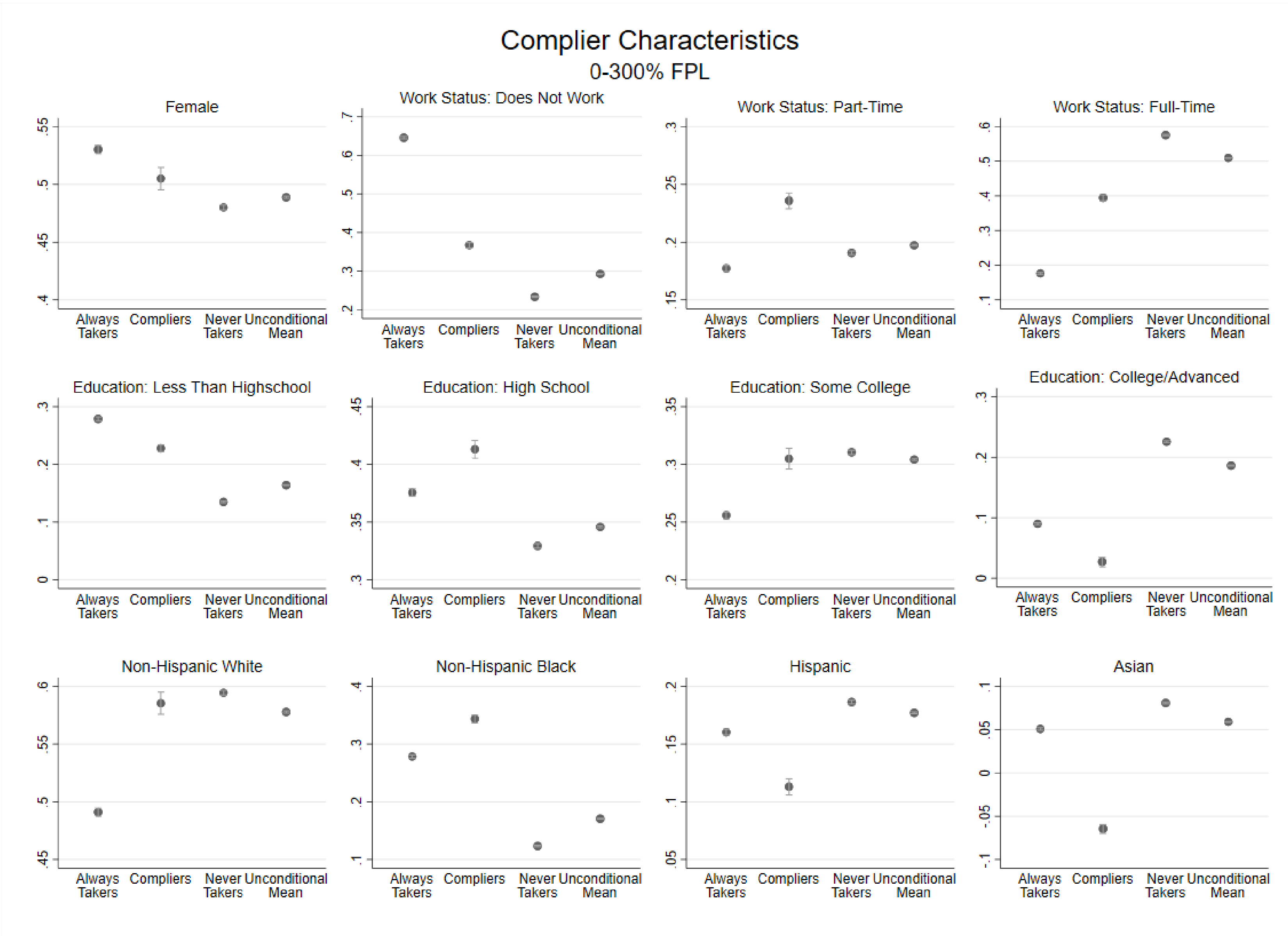


Figure A7: Bacon Decomposition of the ACA Medicaid Expansion: Childless Adults (300% FPL)



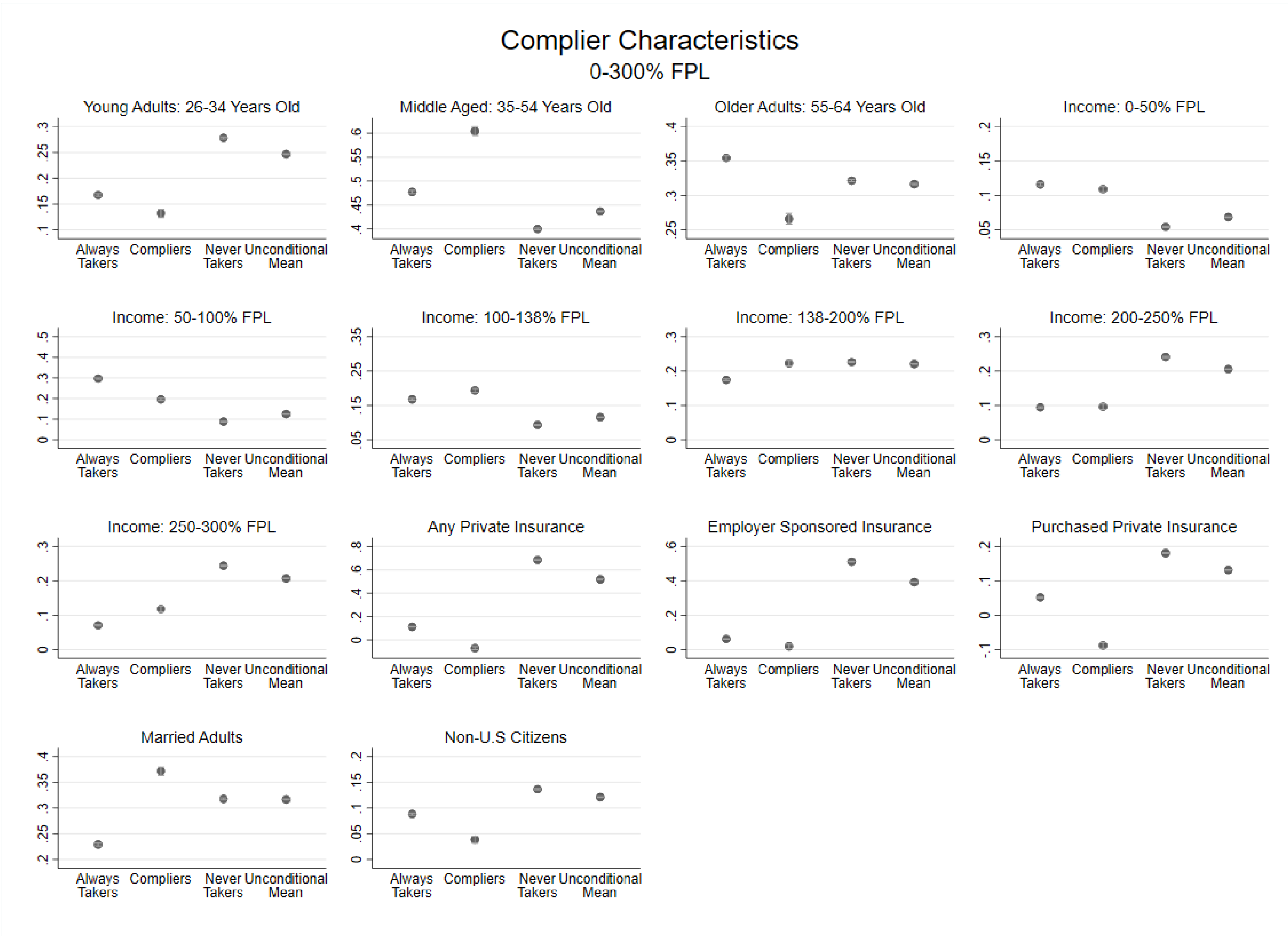
Note: Each panel reports the coefficients from using the DD decomposition outlined in Goodman-Bacon (2021). See section 5.5 for more details.

Figure A8: Observable Characteristics for Always Takers, Compliers and Never Takers: Gender, Work Status, Education, Race, 0-300% FPL



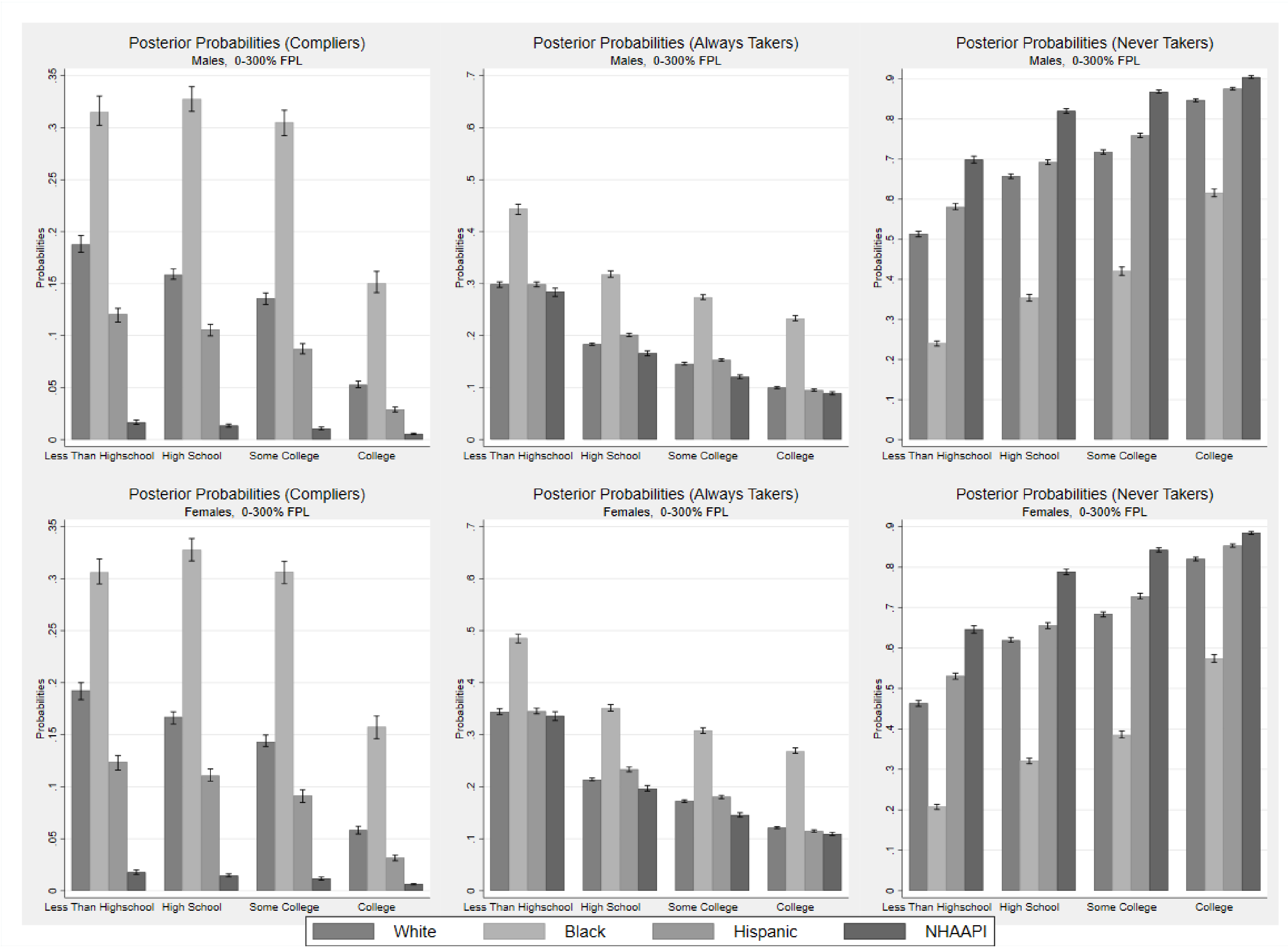
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

Figure A9: Observable Characteristics for Always Takers, Compliers and Never Takers: Age Group, Income Group, Marital Status, Citizenship, 0-300% FPL



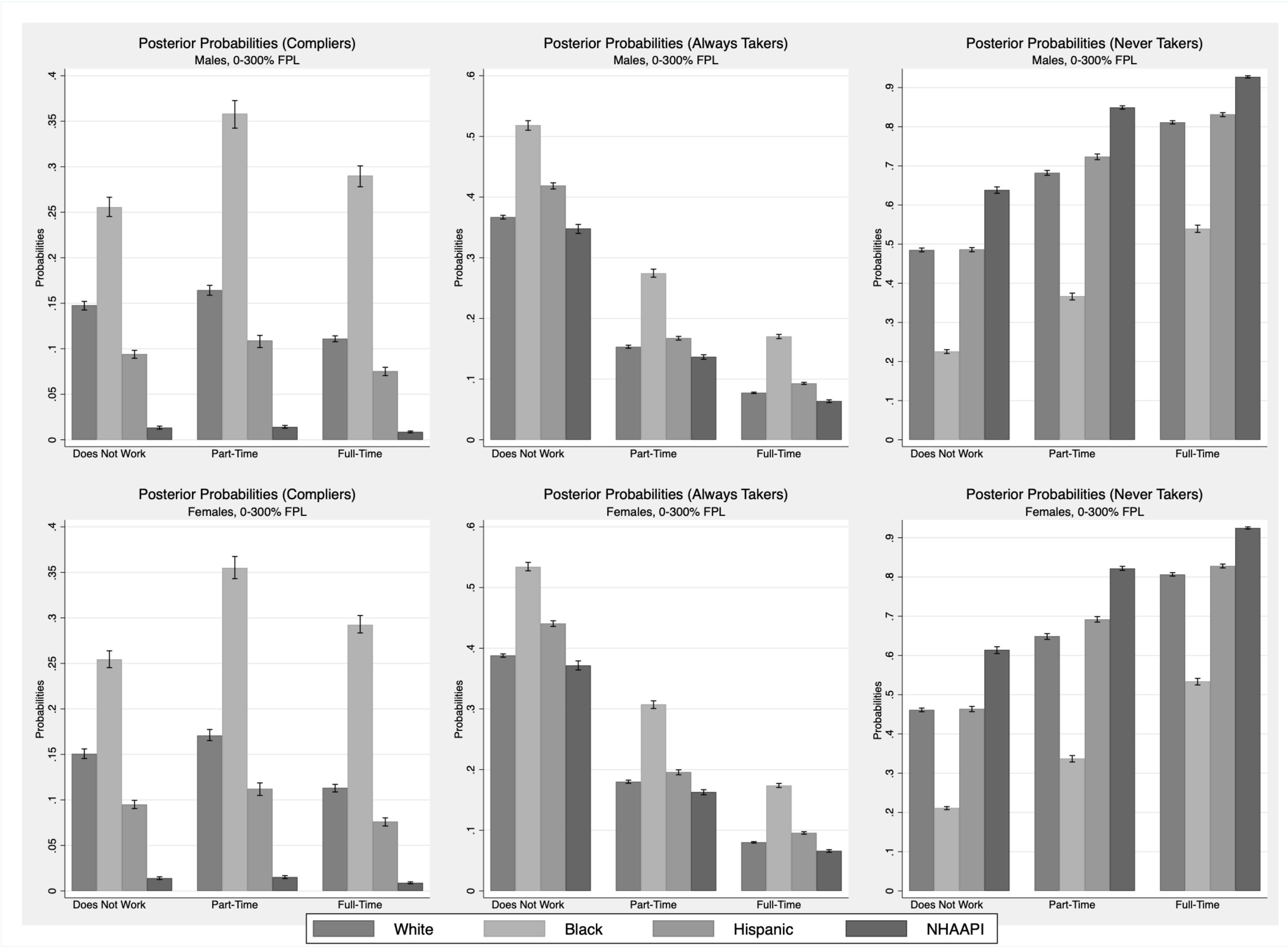
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples. Estimates are reported for each of the groups alongside those for the unconditional mean.

Figure A10: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Education, Race, 0-300% FPL



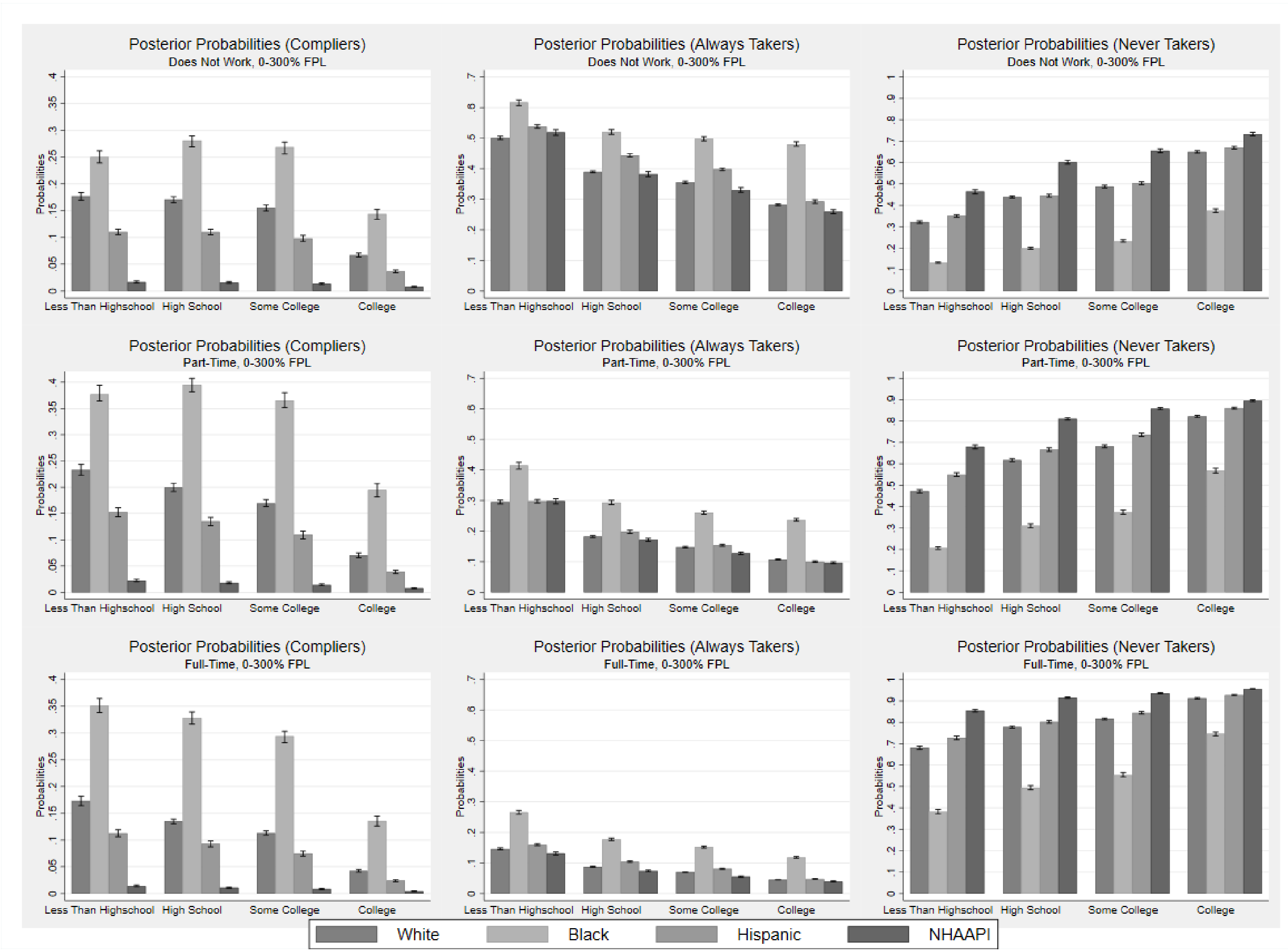
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

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



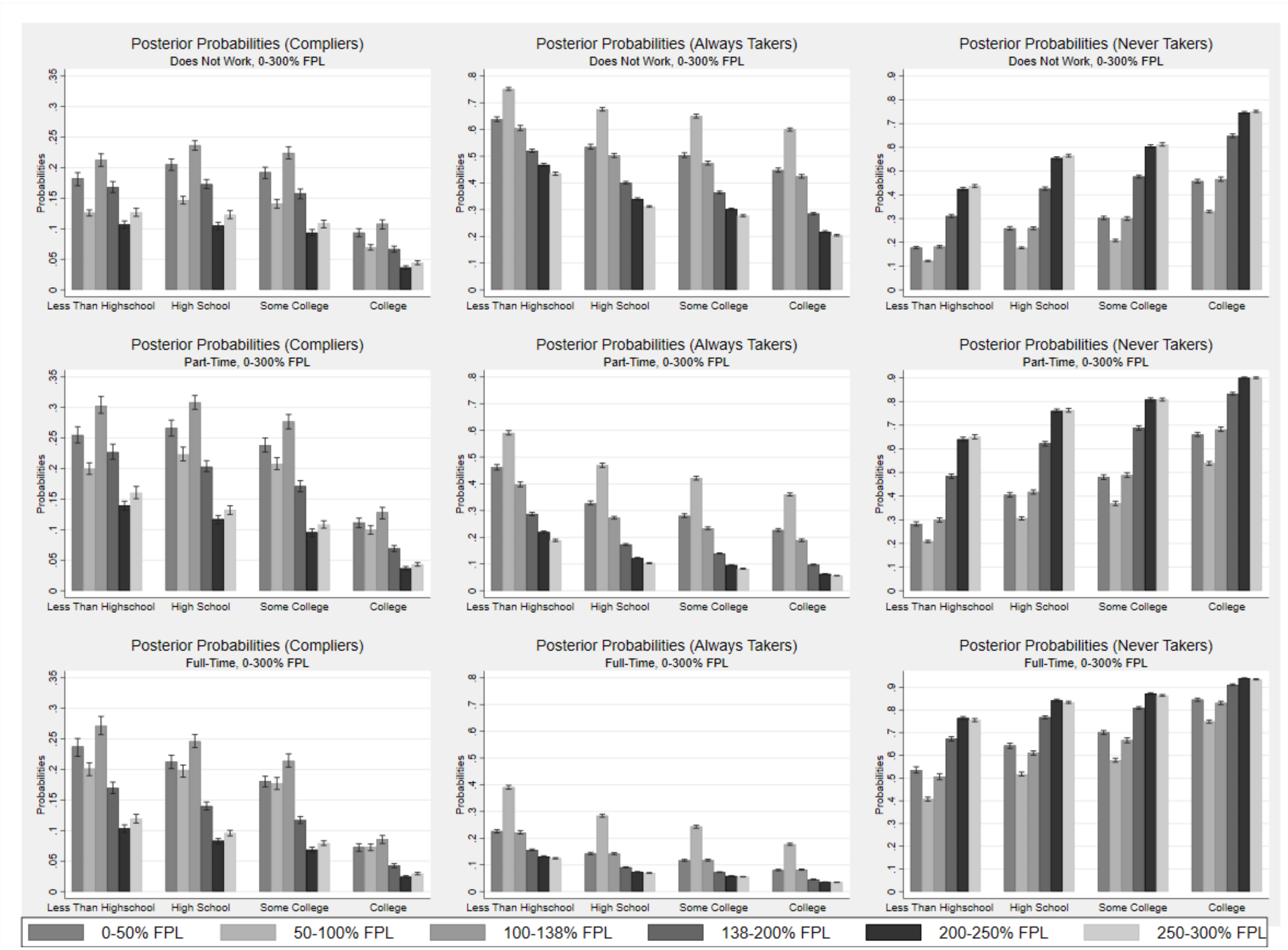
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

Figure A12: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Work Status, Education, Race, 0-300% FPL



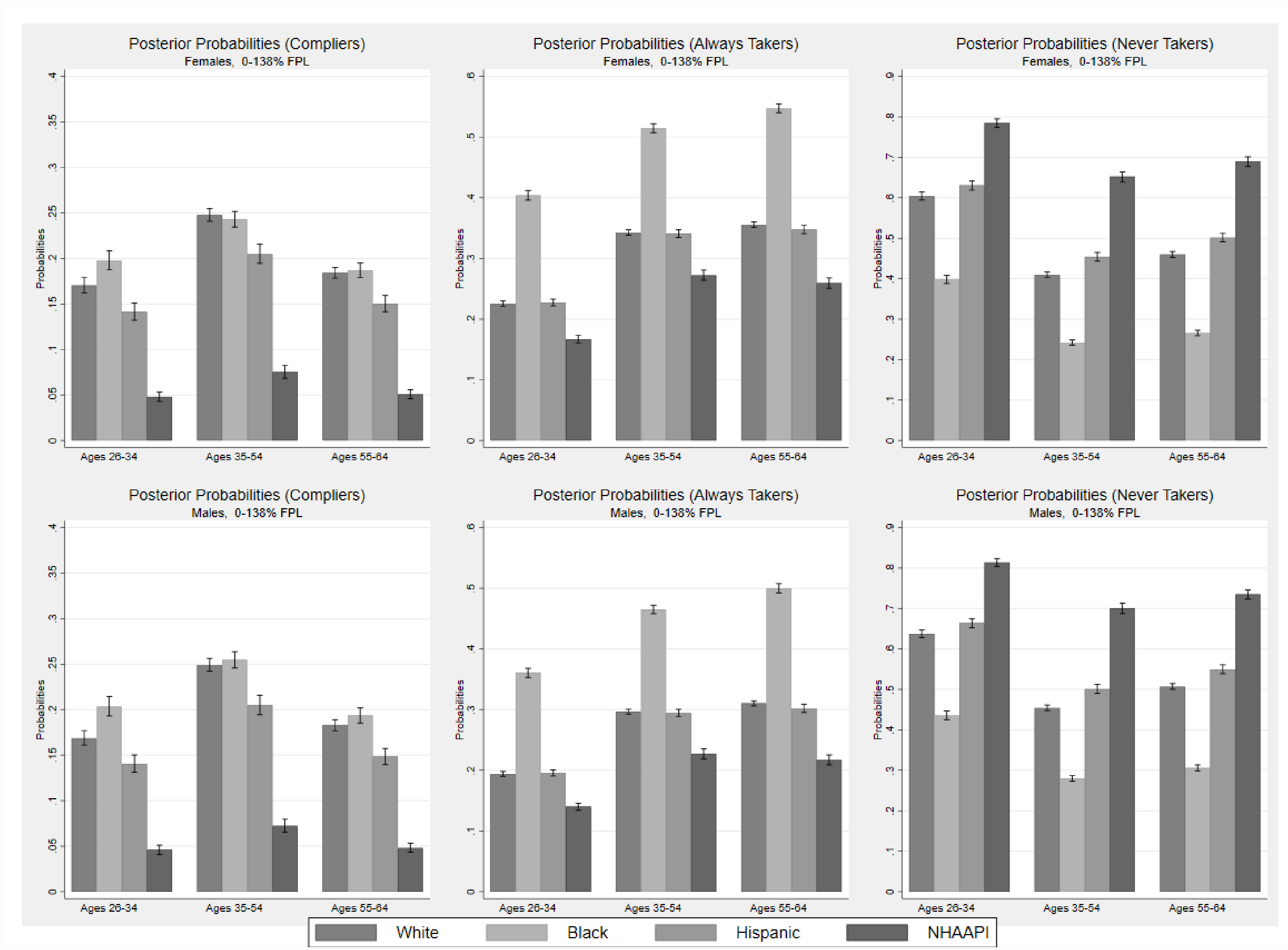
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

Figure A13: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Work Status, Education, Income Group, 0-300% FPL



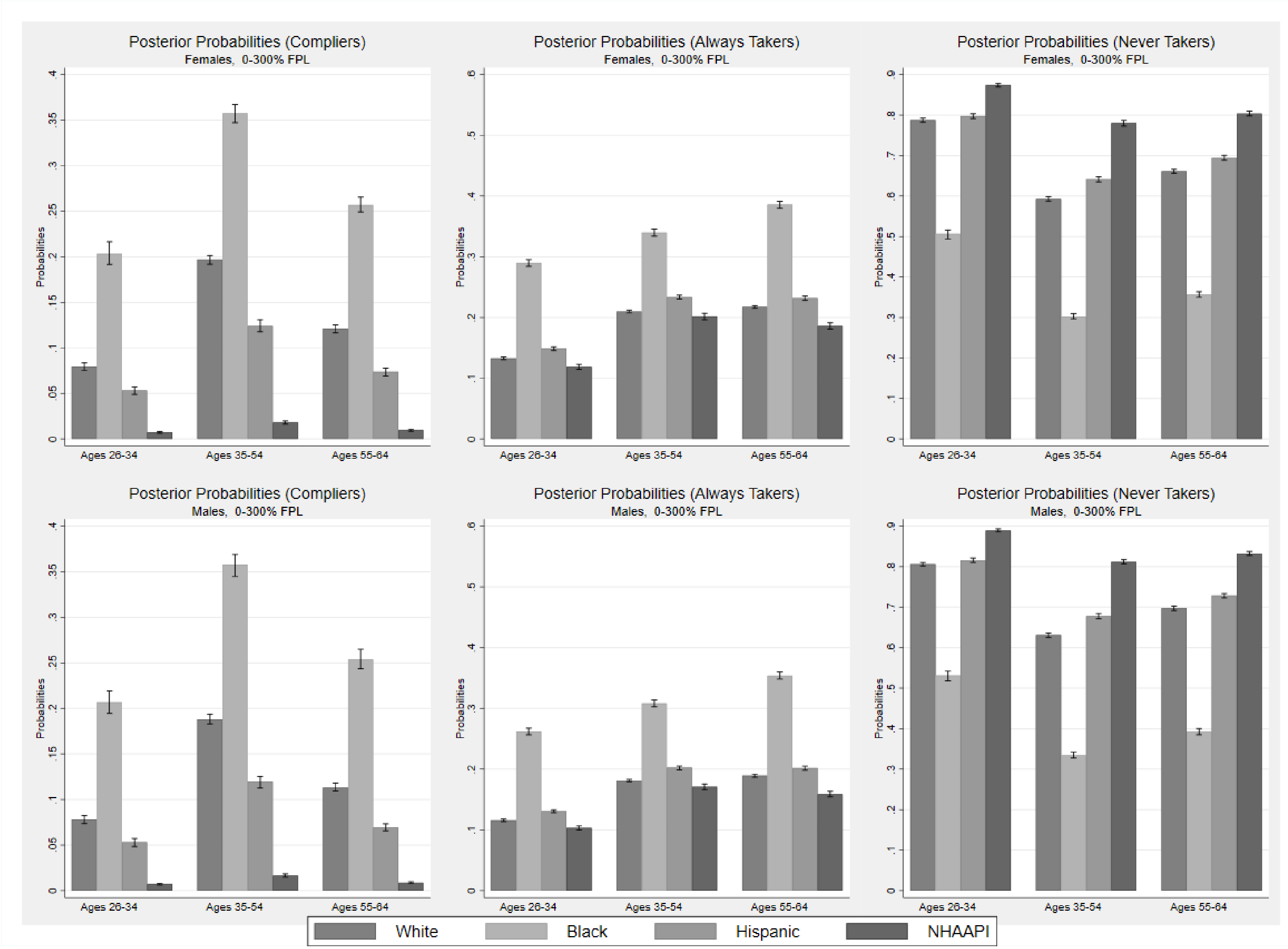
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

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



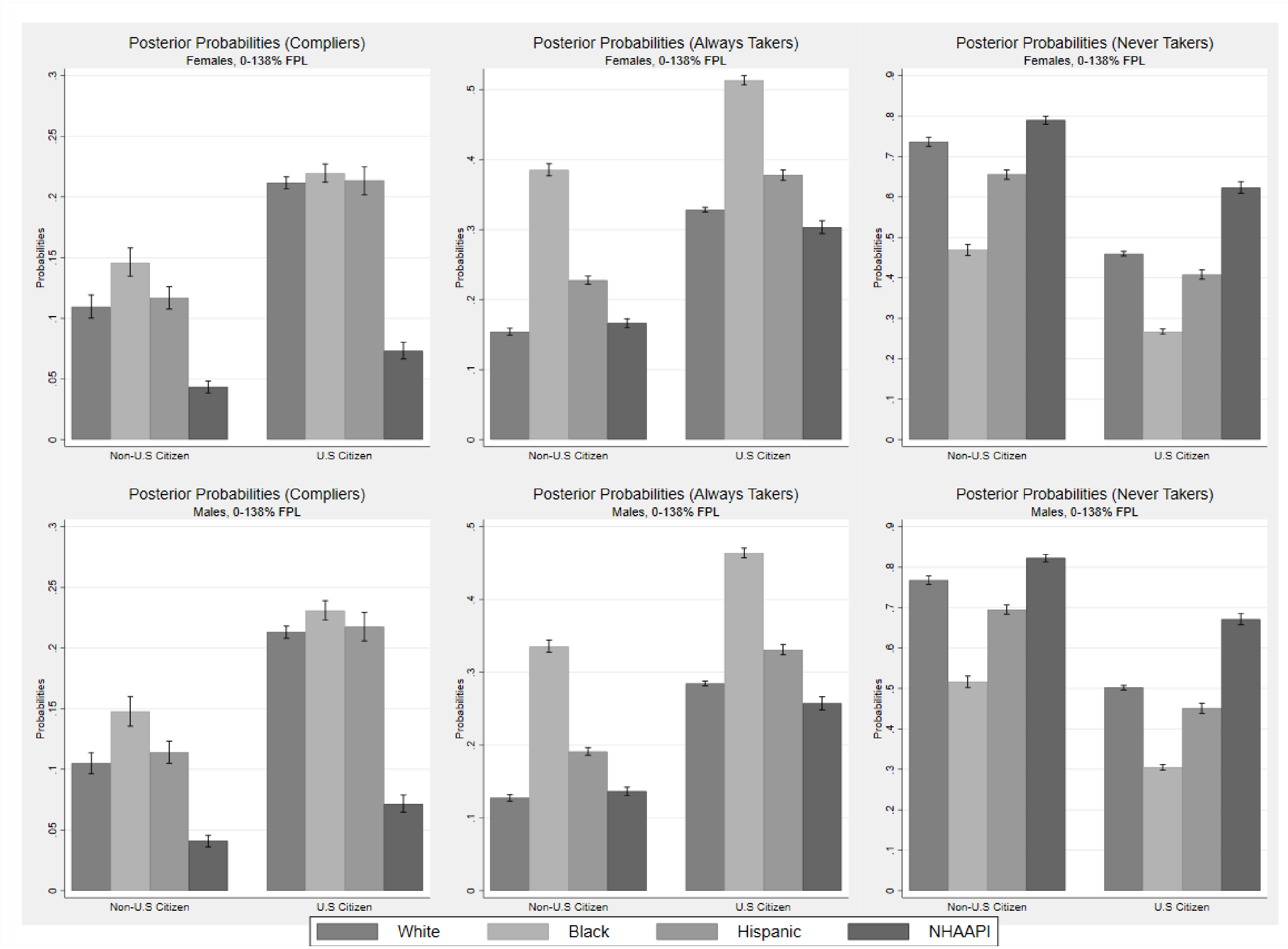
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

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



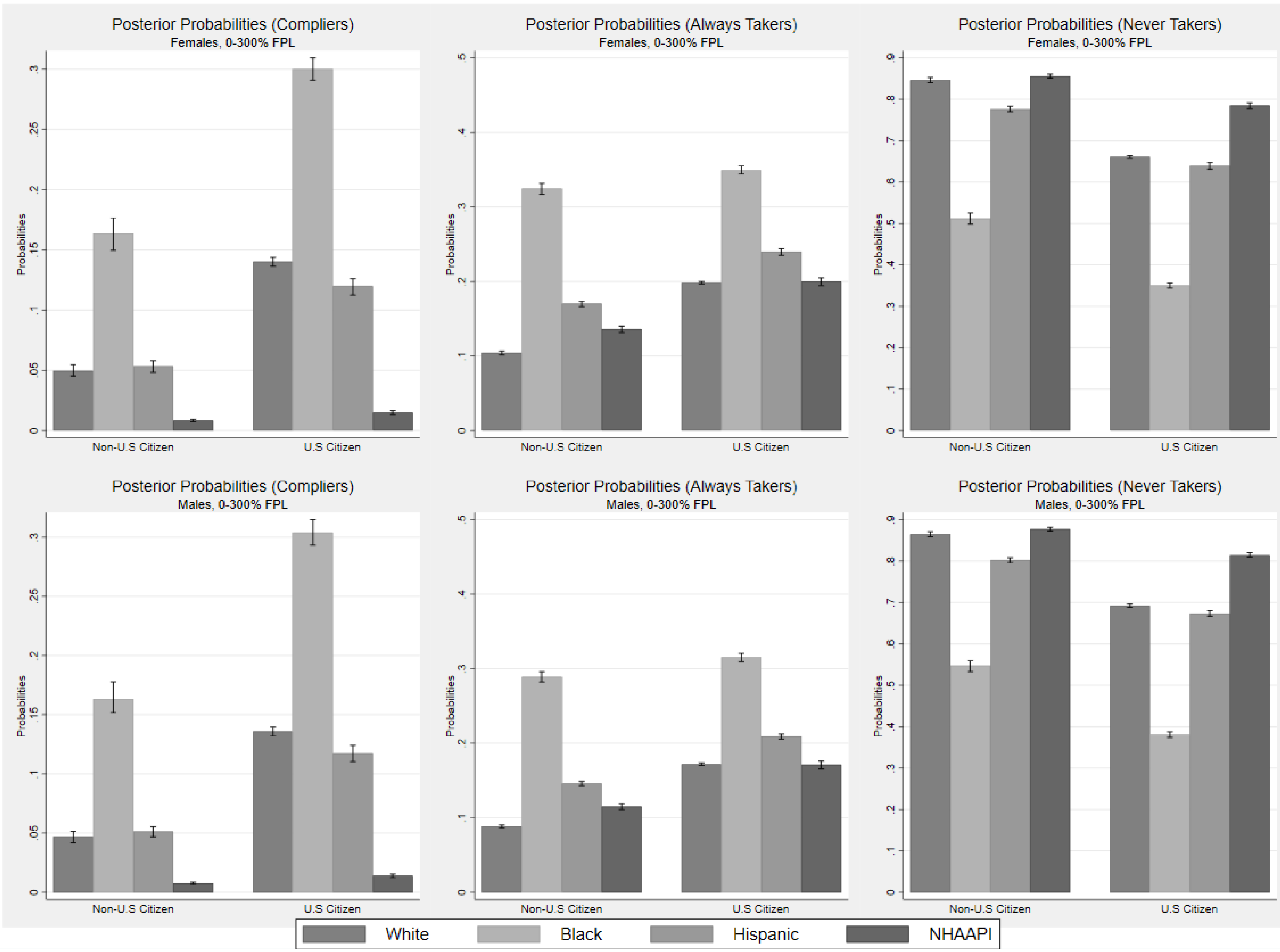
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

Figure A16: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Citizenship, Race, 0-138% FPL



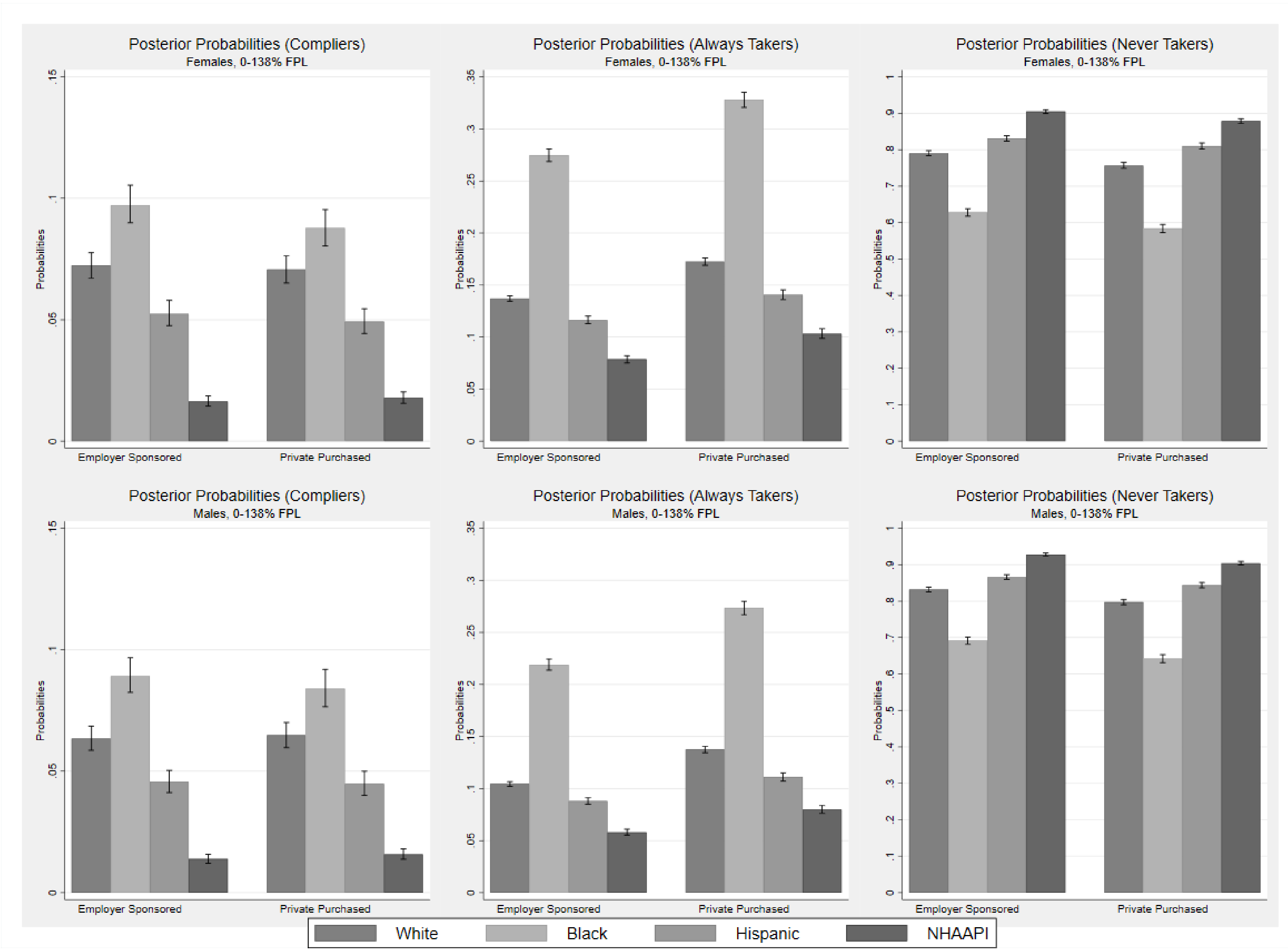
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

Figure A17: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Citizenship, Race, 0-300% FPL



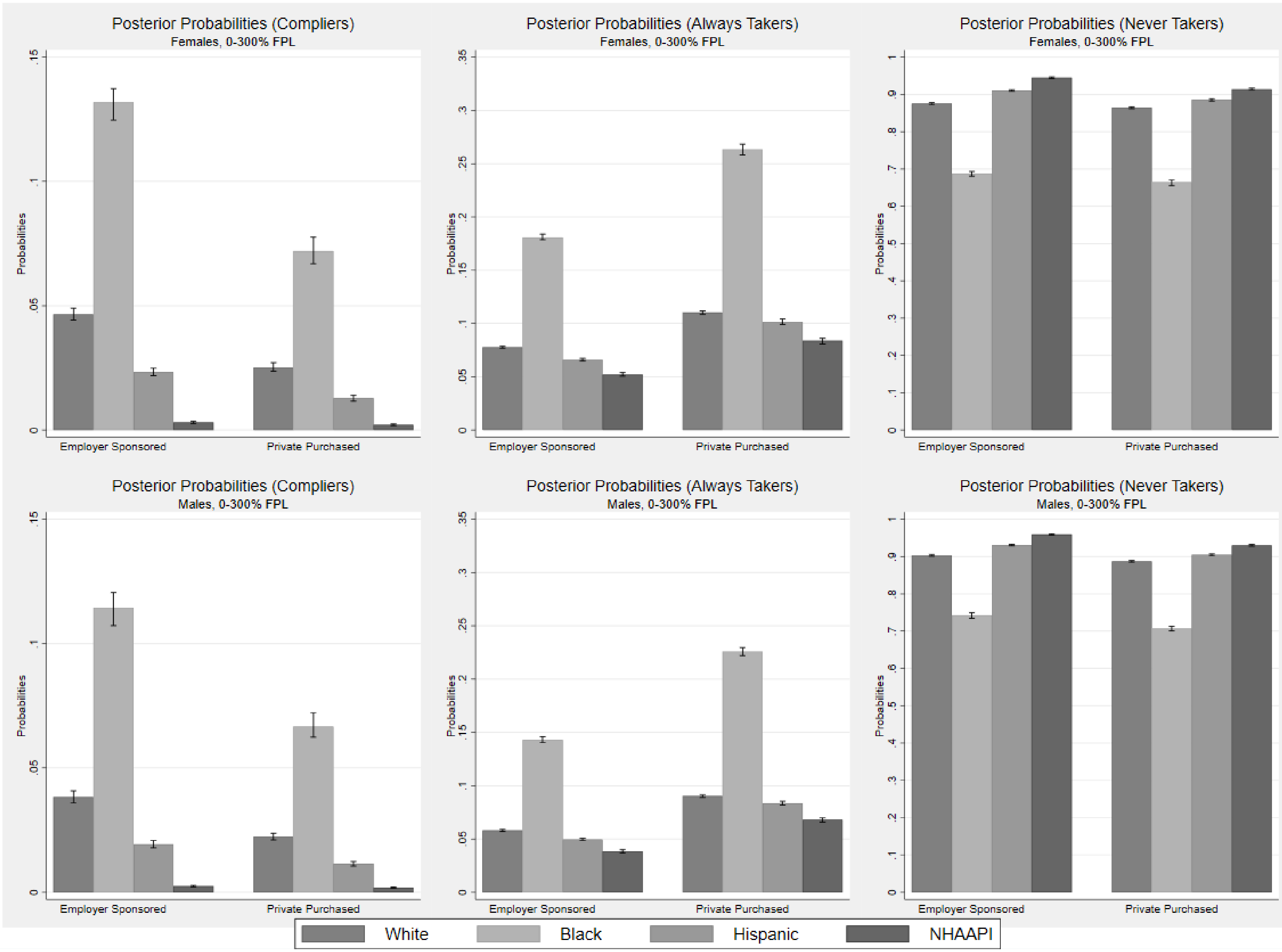
Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

Figure A18: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Private Insurance, Race, 0-138% FPL



Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.

Figure A19: Posterior Probabilities of Compliers, Always Takers, and Never Takers: Gender, Private Insurance, Race, 0-300% FPL



Note: Means and 95% confidence intervals were computed from 1000 bootstrapped re-samples.