The Long Shadow of American Slavery: Its Influence on the Affordable Care Act

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Abstract

This study investigates the relationship between slavery and the efficacy of the Affordable Care Act (ACA) in the American South. Using a Causal Forest approach, the results reveal heterogeneous treatment effects of the ACA-Medicaid expansion, with larger reductions in uninsured rates concentrated in counties with low cotton suitability measures. In Medicaid expansion states, counties more reliant on slavery experienced lower reductions in uninsured rates following the ACA, primarily driven by lower Medicaid coverage among poor Whites. The evidence suggests that current political preferences, as explained by determinants of slavery such as cotton suitability and malaria stability indices, serve as a pathway linking the influence of slavery to the health reform. Moreover, the influence of slavery is attenuated in counties that underwent faster mechanization in the mid-1990s. Overall, findings imply that the legacy of slavery has hindered the implementation of the ACA in the South.

Keywords: The Patient Protection and Affordable Care Act (ACA), Slavery, Institution, ACA-related preferences, ACA efficacy, American South, Politics

JEL codes: P00, P43, P46, I14, D02, B15

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1 Introduction

Passed and implemented during the historic presidency of the first African American president, Barack Obama, the Patient Protection and Affordable Care Act (ACA) has been met with turbulent opposition from the Republican congressmen and lawmakers, governors, Republican candidates and the right-wing media. But nowhere in America has the opposition been as strong as in the American South – twenty one out of the thirty four House Democrats who voted against ACA in the Senate were from the South and many southern states have defaulted to the federal health insurance exchange.[1] Paradoxically, individuals from the Southern region tend to experience comparatively poorer health outcomes, leading to decreased life expectancy, alongside grappling with elevated levels of uninsured rates (Arias et al., 2021; RWJF, 2020).

I investigate the relationship between slavery in the American South and institutional changes in the healthcare sector that are redistributive and equitable in nature by focusing on ACA – the most sweeping healthcare reform in the United States. The goal of ACA was to obtain a nearly universal health insurance coverage through various provisions, including but not limited to the individual mandate, subsidies in the healthcare exchange markets, employer mandate and Medicaid expansions.[2] Following the 2012 supreme court decision that allowed states to decide on Medicaid expansion by making it optional, 29 states participated in ACA-related Medicaid expansion in 2014, with an addition of 7 states joining over the next several years. So far, only 7 out of 16 southern states have implemented Medicaid expansion.[3]

Building on the past literature that links slavery with long-term societal constituents, I propose three conceptual pathways to tie slavery with ACA efficacy. First, I pull from a strand of studies arguing that White Southern elites saw redistributive policies as a subsitute for paternalism that was used as a medium of labor coercion (mainly Blacks) in the postbellum era as Emancipation increased the price for labor (Alston and Ferrie, 1985, 1993). White landowners provided private provisions to public goods (food, medical bills, legal payments) to keep labor cheap, induce loyality, and reduce supervision costs. This created an incentive to resist redistributive programs throughout the Jim Crow era, which finally pleatued following the full-blown mechanization of cotton in 1960s (Alston and Ferrie, 1993). The concentrated culture of resistance in areas historically dependent on slavery can influence the implementation of the Affordable Care Act (ACA).

Next, persistence of political attitudes, values, and preferences transferred across generations

[1] See https://ballotpedia.org/Obamacare_overview

[2] Similar to ACA, the Health Security Act (HSA) proposed by Clinton in 1993 advocated universal health care coverage. The Clinton plan was defeated in 1994 after meeting strong opposition from the Health Insurance Association of America, small business owners, and Republicans who had the control of both the House and Senate in the midterm elections (Dawes, 2016). Knowles et al. (2010) provide evidence that racial prejudice predicted both reluctance to vote for Obama and opposition against ACA, whereas such was not the case with HSA. Tesler (2012) shows that racial attitude was an important variable influencing White Americans' healthcare opinion in 2009-10 and presence of Obama as the president seems to have driven differences in Black-White policy opinions even farther apart compared to the time of HSA.

[3] Southern states in this study include Texas, Louisiana, Arkansas, Missouri, Tennessee, Mississippi, Kentucky, Alabama, Florida, Georgia, South Carolina, North Carolina, Virginia, West Virginia, Maryland, and Delaware; chattel slavery was still legal in these states in 1860.

can determine ACA-related preferences.[4] Acharya et al. (2016) document the legacy of American slavery in shaping current-day political preferences in the American South. The authors argue that the transfer of political attitudes from one generation to the next serves as a significant channel contributing to such persistence. The process of intergenerational transfer may have spilled-over to dictate ACA-related preferences at both personal and institution levels. The alignment of this channel with the paternalistic culture (discussed above) can shape a community's resistance towards ACA-related reforms, thereby influencing the effectiveness of the reform measures.

Third, differences in contemporary factors, as a result of slavery, may shape preferences regarding ACA. For example, White Southerners living in areas more dependent on slavery on average have higher income compared to those in areas less dependent on slavery (Lagerlöf, 2005; Ager et al., 2021). This may increase opposition towards an equity-based healthcare reform among White Southerners in high slavery-dependent areas due to lower perceived benefits from the reform. This channel is consistent with self-interest theory in the literature. It states that as Whites are relatively at a better socioeconomic position compared to minorities, opposition against welfare programs and reforms beneficial to the minorities is driven due to self-interest (Gilens, 1995; Williamson et al., 2011). Finally, theories of racial threat and racial resentment can also help link former slavery to preferences surrounding ACA.[5]

I begin with the exploratory analysis that uses a pooled cross-sectional data from the Cooperative Congressional Election Study (CCES – 2014, 2016, 2018) and Small Area Health Insurance Estimates (SAHIE) merged with the proportion enslaved in 1860. The findings show that the level of slavery dependency is positively associated with White Southerners' preference to repeal ACA. Moreover, uninsured rates fell by lower magnitudes in areas more dependent on slavery. While correlational, these findings offer a strong foundation for further investigation into the relationship between slavery and ACA implementation.

Next, I evaluate the heterogeneous effects of ACA-Medicaid expansion and specifically investigate whether the treatment effects vary across cotton suitability measure – a significant determinant of slavery as established in the literature (Acharya et al., 2016; Williams, 2017; Mazumder, 2021). For this purpose, I use a Machine Learning approach based on Causal Forests (CF) developed in Athey et al. (2019) under the unconfoundedness assumption (i.e., treatment is independent of the potential outcomes conditional on features).[6] The findings demonstrate strong heterogeneity in treatment effects under the Rank-Weighted Average Treatment Effects (RATE) approach (Yadlowsky et al., 2021), with priority scores based on conditional average treatment effect (CATE) estimates. Importantly, areas unyielding to cotton farming experienced sharper declines in uninsured rate following the expansion.

[4] A body of work has provided evidence on intergenerational transfer of political attitude and values (Bisin and Verdier, 2011; Nunn and Wantchekon, 2011; Voigtländer and Voth, 2012; Charnysh, 2015).

[5] This states that to counteract the threats of competition in cases when the size of subordinate group is considerably, the dominant group uses repressive strategies. (Ogburn and Grigg, 1955; Blalock, 1967b; Giles, 1977; Blalock, 1967a).

[6] The analysis is conducted using the Generalized Random Forest (GRF) package. Using several auxiliary analysis discussed in more detail in the results section, I provide suggestive evidence in favor of the underlying assumption.

The subsequent analysis uses data from SAHIE and the American Comunity Survey (ACS) in an event study framework. Specifically, ACS allows assessing the possibility of differential effects across Black and White Southerners by the measure of slavery dependency. In expansion states, the findings from SAHIE demonstrate that areas highly dependent on slavery experienced less improvement in insurance outcomes following the reform, especially among individuals with income below 138% of FPL. This finding is driven by relatively lower increment in Medicaid coverage among poor White Southerners in areas with higher dependency on slavery following the reform, while no differential effects are uncovered for Blacks.[7] Additionally, results in non-expansion states also demonstrate that uninsured rate decreased at a higher rate in low slavery-dependent areas among White Southerners following the reform. These results are robust to instrumenting the proportion enslaved in 1860 using cotton suitability measure, malaria stability index, and proxies for the long-run climate condition (i.e., temperature, precipitation).

To underscore the mechanisms, I present evidence of inertia stemming from historical slavery influences shaping present-day political preferences, subsequently impacting the effectiveness of ACA. In the first approach, I use the variation in the proportion enslaved in 1860 explained by the current-day political outcomes (Trump votes in 2016, White votes for Obama in 2008, whether a county is democrat) using a random forest model. The residual consists of variation in the slavery measure that is unexplained by the current political content. The findings from the event study framework incorporating explained and unexplained variations in slavery show that uninsured rate decreased at a lower magnitude with increases in explained variation in slavery measure, while decreasing at a higher rate with unexplained variation. In the next approach, I employ determinants of slavery (cotton suitability, malaria stability, and the long-run climate conditions) to predict the proportion of White votes attributed to Barack Obama in 2008. In the second stage, I use the predicted values to show that insurance outcomes improved predominantly in areas with higher predicted votes for Obama. Remarkably, the significance of slavery measure diminishes in the same model.

Furthermore, I present evidence indicating that localities historically reliant on slavery, which underwent rapid partial mechanization between 1930 and 1940, demonstrated relatively superior implementation of the ACA. Mechanization of cotton is closely tied to resistance towards redistributive programs. Alston and Ferrie (1985) and Alston and Ferrie (1993) argue that mechanization up-rooted the paternalistic system in South, as the private provision of public goods by White landowners was no longer profitable. The finding is also consistent with pathways presented in the Acharya et al. (2016) study, which documents that Whites residing in counties that mechanized earlier had relatively lower racist sentiments compared to their counterparts.

In Relation to the Literature. This study is related to different strands of studies in the literature. First, it builds on seminal studies developing close ties between slavery and resistance

[7] Since ACS is not a panel, it disallows evaluating the effects based on pre-policy income level. To alleviate concerns regarding endogeneity, rather than focusing on the subset of the sample based on income, I focus on older individuals (age 26 or above) with education level of high school or below. This age group will have surpassed the schooling age by the time of the health reform.

to redistributive programs (Alston and Ferrie, 1985, 1993). The authors contend that emergence of paternalism in slavery dependent areas, following Emancipation, led White Southerners to oppose welfare expansions in the first half of the twentieth century. In a recent study, Mazumder (2021) provides empirical evidence to support the hypothesis developed by Alston and Ferrie (1985) and Alston and Ferrie (1993). Mazumder (2021) finds that spending associated with the New Deal was relatively lower in slavery dependent counties.

This study conceptualizes how the legacy of slavery can obstruct redistributive policies aimed at universalizing healthcare, even when implemented 150 years after abolition. As such, it directly relates to the literature discussing barriers to implementing universal healthcare reform in America. Opponents of universal healthcare reform frequently cite drawbacks or barriers such as excessive costs coupled with potential tax increases, logistical complexities, concerns about inefficiency resulting in diminished quality of care, and the diverse demographic with varying health-related needs (Light, 2003; Sessions and Lee, 2008; Fuchs, 2013). Beyond these challenges, the findings of this study document persistent influence of former oppressive institutional regimes in creating barriers to implementing healthcare reform directed towards universalization.

The study is also related to the growing literature that investigates the relationship between the former slavery and economic as well as political outcomes (Lagerlöf, 2005; Naidu, 2012; Bertocchi and Dimico, 2014; Hornbeck and Naidu, 2014; Acharya et al., 2016; Williams, 2017; Mazumder, 2021). A segment of the study builds on Acharya et al. (2016), which investigates the long-run political persistence of the American slavery. Given the racial discrimination and strong opposition to the ACA in the American South, it is important to investigate whether the effectiveness of equity-based healthcare reforms like the ACA is influenced by the legacies of oppressive institutions. More broadly, this study builds on previous work demonstrating the long-term effects of institutions, historical events and episodes (Nunn, 2008; Nunn and Wantchekon, 2011; Voigtländer and Voth, 2012; Acharya et al., 2016; Dell et al., 2018).

Third, this study contributes to a handful of studies emphasizing the role of path dependency in determining future health policies and reforms following critical junctures (Jacobs and Skocpol, 2011; Haeder, 2012; Fouda and Paolucci, 2017). While Jacobs and Skocpol (2011) and Haeder (2012) argue that the ACA serves as a critical juncture in the U.S. healthcare system by significantly altering the trajectory of health policies, we take a different position. We explore whether discriminatory past institutional settings shape the efficacy of pro-equity health reforms such as the ACA.

The study proceeds as follows. Section 2 provides a conceptual framework discussing the legacy of the American slavery in shaping ACA-related preferences and its efficacy. Section 3 documents various data sources used in this study. Sections 4 and 5 discuss various empirical methods and findings, respectively. Section 6 underscore the potential mechanisms, while section 7 concludes.

2 Conceptual Framework

Even after 150 years from the Emancipation Proclamation, nowhere in America was the opposition against ACA as turbulent as in the American South. Only two out of the 16 southern states have operated their own exchanges, and all states in the Deep South rejected Medicaid expansion in 2014. Rick Perry (the Republican governor of Texas) and Rick Scott (the Republican governor of Florida) are well-known to have posed vehement opposition against ACA. Additionally, Florida's Republican attorney general was the first to file suit against ACA, which eventually turned out as the Supreme Court case. Eight out of sixteen southern states challenged ACA on both constitutionality of the individual level mandate and Medicaid expansion, with Virginia being the sole state not to challenge the Medicaid expansion reform (Kaiser Family Foundation, 2012). While five other southern states declared no position, only Maryland supported the reform.

I first build on the framework of private provision of public goods established in seminal studies (Alston and Ferrie, 1985, 1993) to explain the link between slavery and ACA efficacy. Following Emancipation, White Southern landowners gained economic incentives to maintain landload-labor relations by engaging in paternalism. The provision of in-kind payments tied to the paternalistic tradition helped lower the price of labor, decrease supervision costs, and foster loyalty. The core functioning of the paternalistic system was rooted in racism, made eplicit following Reconstruction and throughout the Jim Crow era. Laborers, mainly Blacks, depended on White landowners for security and livelihood. In these circumstances, the expansion of the welfare system served as a substitute for paternalism and posed a threat to existing labor relations. This led White Southern elites to vehemently oppose redistributive programs. The mechanization of Southern agriculture in the 1960s reduced the incentive for paternalism (Alston and Ferrie, 1993). However, the culture of resistance towards the welfare state coupled with the racialization of the ACA (discussed below) can provide a strong link between slavery and the efficacy of the health reform.

Race-targeted policies such as affirmative action and federal aid to minorities have known to implicate *racialization* – a process in which racial attitudes inform policy preferences. Despite President Obama's attempt to deracialize the reform to gain approval of the American public, racialization of the reform may have been evoked through political messages and mass communications linking the reform to racial groups (minorities) as well as the intent of the reform to address racial and ethnic disparities (Michener, 2020). Moreover, since the background characteristics of elite sources can advocate race-based preferences,[8] Racial symbolism surrounding Obama can spillover to inform preferences towards the ACA.[9]

[8]Studies show that political person's race, religion, and gender can create group-based opinions. For instance, Jacobson (2007) suggests that George W. Bush's identification as a born-again Christian led to an increased support for the Iraq war among White evangelicals. Similarly, Winter (2008) argue that gender-based attitude influenced healthcare reform debate in 1993-1994 due to the reform's strong attachment to Hilary Clinton.

[9]Tesler (2012) terms this process as *spillover of racialization.* Knowles et al. (2010) conclude that racial prejudice predicts both indisposition towards voting for Obama and opposition towards "Obama Care", while racial prejudice cannot explain preferences regarding the Health Security Act – a reform roughly similar in nature to ACA but devised during the presidency of Bill Clinton. Similary, Tesler (2012) argue that racial attitude was an important determinant of White Americans' preferences towards the healthcare reform in 2009 and its influence only grew in the upcoming

Next, I draw from the theories of *racial resentment (symbolic racism)* and *racial threat* in the context of racialization of ACA to explain the linkage between historical slavery and ACA implementation. The theory of *racial resentment* argues that White Americans' negative attitude towards policies disproportionately favoring minorities are driven by the belief that "racial discrimination is largely a thing of the past" and Blacks have not worked hard enough to attain both economic and social success (Kinder and Sanders, 1996; Sears et al., 1997). Consistent with this theory, Lanford and Quadagno (2016) find that the state level racial resentment negatively affects a state's adoption of ACA-related Medicaid expansions. Similarly, scholars have highlighted the concept of *racial threat* based on demographic composition. In other words, as the size of the subordinate group grows to be considerably large, the dominant group counteracts competition using racial hostility and repressive strategies (Ogburn and Grigg, 1955; Blalock, 1967b; Giles, 1977; Blalock, 1967a). This is emphasized by Key (1984), "...To maintain its own status the ruling group must oppose any political program that tends to elevate or excite the masses, Black or White."

Grogan and Park (2017) adjoin both of the aforementioned theories together to form an Integrated Racialized Backlash theory. The authors show that the state's decision of whether to expand Medicaid depends on the level of support from the White populace, whereas the support from non-Whites tend to be impertinent. More importantly, states with a higher proportion of Blacks are less likely to expand Medicaid in instances of low levels of support from Whites. In fact, Mississippi, Georgia, South Carolina, and Louisiana all decided not to expand Medicaid in 2014 despite the majority of public favoring expansion (see Grogan and Park (2017)).

The abolition of slavery exacerbated economic loss in the American South due to the Civil War, which was mainly borne by White Southern elites (Ransom and Sutch, 2001). This influenced racial politics in South as a result of which the White Southern elites formed an institution of Jim Crow to preserve power. The Jim Crow laws and de facto exclusionary laws such as the poll taxes and literacy test disproportionately suppressed Blacks' social, economic, and political involvement. During the Jim Crow segregation era, White children were constantly exposed to the rhetoric of White supremacy at home as well as public schools and were active witnesses of racial violence in public spaces (DuRocher, 2011). In other words, the channel of persistence argues that racial resentment is not simply the component of the present but is linked to the past. The culture of racial resentment can transfer over the generations to shape contemporary opposition against an equity-based healthcare reform such as ACA.

A large body of work in economics and political science has highlighted the transfer of political attitudes, values, and preferences from parents and older relatives to children (Bisin and Verdier, 2011; Nunn and Wantchekon, 2011; Voigtländer and Voth, 2012; Charnysh, 2015; Acharya et al., 2016). Cultural anthropologists Boyd and Richerson (1996) and economists Bisin and Verdier (2011) argue that one reason why cultural changes happen so slowly is due to the transfer of cultural traits from parents to children. Several past studies have also demonstrated empirical evidence regarding the persistence of political attitudes, cultural traits, and values over the generations.

years.

Voigtländer and Voth (2012) show that areas with a higher concentration of plague-era pogroms also demonstrated higher levels of anti-Semitism in the 1920s. Similarly, Charnysh (2015) argues that anti-Semitic cues disseminated by populist elites in Poland in the years leading up to the 2003 EU referendum resonated strongly with voters who were predisposed to anti-Semitism.

The context of racial oppression in the American South is no exception to the pattern of cultural persistence. Acharya et al. (2016) show that *i*) areas with higher dependency on slavery are more likely to have White Southerners who show racial resentment against Blacks and oppose policies that benefit the minorities; and *ii*) the content of racial resentment following the Emancipation and the end of Reconstruction has been transferred over the generations to shape contemporary political attitude. In a similar context, Williams (2017) demonstrates that areas with high historical lynchings have subdued contemporary political participation among Blacks. These patterns of persistence can spillover to form preferences regarding ACA.[10] In short, deeper roots of historical racial oppression can directly influence the implementation of ACA through political persistence.

Some distinct similarities can be drawn regarding forces driving the opposition towards ACA and other equity-based policies that has either been explicitly opposed or historically racialized in the American South. Examples include opposition to the New Deal and that of school desegregation. As previously mentioned, building on the contention of Alston and Ferrie (1985), Mazumder (2021) provide evidence that spending associated with the New Deal was lower in areas more dependent on slavery. Next, the affirmation of school desegregation by the Supreme Court following the wake of *Brown v. Board of Education* (1954) led to the emergence of intransigent segregationist, who interposed *Brown* as an abuse of judicial power that would lead to a collapse of the Southern culture (Day, 2014). The doctrine of the Southern Manifesto, signed by 100 southern politicians in opposition to racial integration, also served as a "political and legislative strategy to sustain Jim Crow" (Day, 2014).

3 Data

I compile data from various sources to conduct the analysis.

[10] A strand of literature also evaluates the persistence of former slavery in shaping the current-day human capital outcomes in the South. Lagerlöf (2005) demonstrates the geographic disparity in income across the southern landscape such that income disparity between Whites versus Blacks is more pronounced in formerly slave dependent areas. Ager et al. (2021) show that White households that held more slaves in 1860 were able to recuperate their loss of wealth following the abolition of slavery by 1900. Moreover, by 1940 the grandsons of slave-owning households surpassed their counterparts in human capital outcomes such as educational and occupational attainment. Additionally, Althoff and Reichardt (2022) show that Jim Crow regimes considerably reduced Black families' economic progress and contributed to the gap in human capital outcomes between Black families who were enslaved until the Civil War versus those Black families who were freed before the Civil War.

3.1 Outcome Variables of Interest

The variable used to define preferences towards the ACA comes from the Cooperative Congressional Election Study (CCES) of 2014, 2016 and 2018.[11] Specifically, I use a question regarding ACA that is consistently reported in both 2014 and 2016 survey years: *Would you vote to repeal the Affordable Care Act if you were in Congress today?* Based on this question, I construct an indicator representing "against ACA," which includes people who are inclined to repeal the reform. ACA-related questionnaires in 2018 are more detailed and ask whether the respondent would: *i*) Repeal the entire ACA; *ii*) Repeal the part of ACA that requires that most individuals have health insurance; and *iii*) Partially repeal ACA (this includes repealing the individual and employer mandates and cut Medicaid payments by 25%). In the 2018 CCES survey, I use whether respondents are in favor of repealing the entire ACA to construct a more conservative measure of preference against the ACA. I then pool the data from CCES surveys (years 2014, 2016, and 2018) and aggregate data at the state level using survey weights.

To measure the efficacy of ACA implementation this study examines reductions in uninsured rate, increases in Medicaid coverage, and increases in federal CHIP-Medicaid funds following the ACA. I use the county-level uninsured rate from the Small Area Health Insurance Estimates (SAHIE) for the years 2010 to 2018 pertaining to the overall population of 18 to 64 year olds as well as for the sub-groups defined by the following income categories: *i*) below the 138% of the FPL, *ii*) between 138% and 200%, *iii*) between 200% and 250%, *iv*) between 250% and 400%, and *v*) above 400% of FPL. However, insurance coverage by racial groups and insurance types are not publicly available in SAHIE dataset.

To complement the analysis, the study utilizes detailed insurance coverage data ACA from the American Community Survey (ACS) one-year sample files for the years 2010 to 2018.[12] Using information provided in ACS, I create binary variables to indicate whether an individual had: *i*) any insurance coverage (uninsured status), *ii*) employer sponsored insurance coverage, *iii*) Medicaid coverage, *iv*) private insurance coverage, or *v*) other forms of insurance. These variables are aggregated at the Public-Use Microdata Area (PUMA) level by Black and White race groups across years, using within PUMA-year sample size as weights.

Data for the federal Medicaid-CHIP transfers comes from the Bureau of Economic Analysis (BEA). BEA estimates the total value of federal Medicaid-CHIP transfers allocated for each county. To construct the federal Medicaid-CHIP transfer per person living below the federal poverty level I

[11] The primary aim of the CCES is to understand Americans' perspectives on the Congress, political representatives, voting behavior and their views regarding social policies. The survey includes a large enough sample, which enables us to isolate Southern region alone and still have enough sample size for the purpose of descriptive analysis.

[12] Several attributes make ACS files particularly useful. First, the ACS consistently reports information on health insurance coverage starting from 2008, further broken down by the types of insurance (e.g., private, current or former employer, Medicaid, Medicare, Tricare, Indian reservations, VA). Second, the publicly available surveys include local-level area identifiers, Public-Use Microdata Areas (PUMAs), which aids in operationalizing the identification strategy of this study. PUMAs' boundaries are updated in every 10 year period based on Census population estimates. As such, ACS from 2012 onwards rely on the 2010 PUMA demarcation. To align ACS data from 2010 and 2011 (which use the 2000 PUMA boundaries) with the 2010 PUMA boundaries, we use crosswalk files. See `https://usa.ipums.org/usa/volii/pumas10.shtml` for more detail.

divide the total transfer amount by the county-level population living in poverty for the year 2000. Data for Medicaid-CHIP transfers are obtained from the Olvera et al. (2023) study replication package.

3.2 County Level Variables

Several county level variables are used to supplement the main findings of the study, including both historical and contemporary characteristics. The historical variables include:

- Percentage of enslaved population in 1860
- Percentage of free Black population in 1860
- Percentage of Black sharecroppers in 1930
- Cotton suitability measure
- Malaria stability index
- Total population in 1860
- Proportion of small farms in 1860
- County area in 1860
- Average farm value per acre of an improved land in 1860
- Total acres of improved farmland in 1860
- Access to railroad and waterways in 1860
- Lynching rate (total number of lynchings, 1882–1930 divided by 1920 county population)
- Value of tobacco, cotton, rice, or sugar as the percent of the total agricultural output in 1860
- Percentage of Democrat votes in presidential elections between 1880 to 1964
- Number of Rosenwald schools
- Total expenditure pertaining to the Hill-Burton project between 1947 and 1971
- County-level health departments (CHDs) between 1908 and 1933.

The contemporary variables include:

- Proportion of Blacks and Whites in 2010
- Total population in 2010

- Estimated White vote share for President Obama
- Vote share for President Trump
- Whites' household income at age 35 from the Opportunity Atlas
- Per capita income in 2000 and 2010
- Poverty rate in 2010
- PM 2.5 measure in 2010
- Percent with college (high school) degree in 2010
- Unemployment rate 2010
- Infant mortality per 1,000 births (averaged for the years 2010-2013)
- Rural-urban classification

Additionally, geospatial variables such as latitude, longitude, land ruggedness and elevation of a county's centriod, and long-term averages of temperature and precipitation are used as features. The data sources of the county level variables are discussed in more detail in the Appendix section A.

Figure 2 displays the map showing the proportion enslaved at the county level in 1860. Figure 3 illustrates descriptive relationships between historical slavery, sentiments to repeal ACA, and the reform's efficacy. As shown in Figure 3, panel A, White Southerners' sentiments to repeal ACA is positively associated with dependency on slavery. States with higher dependency on slavery also show a higher proportion of Whites in favor of repealing the ACA but no such relationship exist for Black Southerners (panel B). Moreover, as illustrated in panels C and D, improvements in uninsured rate as well as increases in Medicaid transfers following the reform are strongly correlated with the proportion enslaved in 1860. Although correlational, these evidence provide a robust foundation for constructing a framework that links historical slavery to the contemporary effectiveness of the ACA.

4 Methods

I begin with the analysis to investigate the heterogeneous effects of Medicaid expansion. The objective is to examine the varying impacts of the policy on reducing the uninsured rate based on the measure of cotton suitability, which is recognized as a significant indicator of historical slavery intensity. Next, I discuss the event study method to inspect the relationship between the proportion enslaved in 1860 and ACA implementation both in Medicaid expansion versus non-expansion states. This is followed by the discussion of instrumenting slavery measure using cotton suitability index, malaria stability, and climate-related variables.

4.1 Heterogeneity of Medicaid expansion policy

Causal Forest. I use causal forest (CF) developed within the Generalized Random Forest framework in Athey et al. (2019) to evaluate heterogeneity of Medicaid expansion in the American South. In summary, CF uses adaptive weights based on random forest to evaluate treatment effect by systematically weighting observations in the R-learner framework. The R-learner framework, formally discussed in Nie and Wager (2021), is based on the decomposition originally proposed by Robinson (1988) to estimate parametric components in a partially linear models. The model is written as:

$$Y_i - m(X_i) = \tau(X_i)(W_i - e(X_i)) + \epsilon_i \tag{1}$$

where Y_i is the outcome variable documenting ACA efficacy (i.e., uninsured rate) in county i. The main effect ($m(X_i)$) is defined as $m(x) = \mu_0(x) + e(x)\tau$, where $\mu_0(x)$ is the baseline conditional expectation without the treatment. $W_i = \{0,\ 1\}$ is the treatment indicator (whether a county belonged to the expansion state), and the propensity score is given as $e(X_i) = P(W_i = 1|X_i)$. $\tau(X_i)$ is allowed to vary with X_i or the features. This very aspect is the focal point for heterogeneous treatment effects.

$\tau(X_i = x)$ is identified as the conditional treatment effect (CATE) under the assumption of unconfoundedness: $Y_i^{(0)},\ Y_i^{(1)} \perp W_i|X_i$. In other words, controlling for covariates makes the treatment assignment as good as random. The observed confounding factors are orthogonalized from both the outcome and treatment variables, which produces the residual-on-residual regression as given above. Moreover, Chernozhukov et al. (2018) show that orthogonalization can help alleviate regularization bias that originates from many ML methods shrinking the importance of features to reduce complexity.

The intuition of how equation 1 works is as follows. Units with similar Xs will have similar estimates for $m(x)$ and $e(x)$ across both treatment and control groups. Now, consider that the treatment effect is positive; this will show up in Y_i; $Y_i - m(x)$ will be higher for $W = 1$ compared to $W = 0$ for the similar estimates of $m(x)$. On the other side, $W_i - e(x)$ is positive for $W = 1$ and negative for $W = 0$ for the similar estimates of $e(x)$. Such variations in the left and right hand side quantities will allow us to capture positive estimates on $\tau(X_i)$.

One challenge is that both $m(X_i)$ and $e(X_i)$ are not known in practice and need to be estimated. Chernozhukov et al. (2018) advocate cross-fitting to estimate the nuisance functions (i.e., $m(.)$, $e(.)$). The CF framework estimates $m(X_i)$ and $e(X_i)$ using random forest where predictions are carried out using the out-of-bag (OOB) sample. Moreover, regression trees in the GRF framework are based on *honest splitting*, which randomly divides the sample into two halves, using one segment to train the model and other to cast predictions. By its inherent nature, this addresses the necessity for cross-fitting to prevent overfitting.

The next important aspect of CF is the use of random forest as an adaptive neighborhood finder for the test sample x. While the standard random forest model for regression typically performs splits to maximize the difference in means across two child nodes such as Breiman et al.

(1984)'s Classification and Regression Trees (CART) algorithm, the CF algorithm encodes the need to maximize the difference in treatment estimates when splitting a parental node.

Theoretically, this means that for each potential axis aligned split that extends from the parent node, one would need to estimate treatment effects at two of the child nodes (τ_L and τ_R) and choose the split that maximizes the squared difference between child specific treatment effects. However, in practice this is highly computationally demanding and infeasible. The application of causal forest estimates τ_P at the parent node and uses a gradient-based function to guide the split. At each (parent) node the treatment effect is estimated only once.[13]

Given the test point x, the goal is to provide higher weights to observations that are similar to x and lower weights to those that are not similar when estimating equation 1. The tree specific weight for a training observation i at the b^{th} tree is given as: $\alpha_{ib}(x) = \frac{1(X_c \in L_b(x))}{|L_b(x)|}$, where $L(x)$ is the leaf (neighborhood) that consists the test sample x. The forest is composed of B trees and the forest specific weight for an example i is given as: $\alpha_i(x) = \frac{1}{B}\sum_{b=1}^{B} \frac{1(X_i \in L_b(x))}{|L_b(x)|}$.[14] It measures the fraction of times an observation i falls on the same leaf as x in the course of the forest. Simply, it shows how similar X_i is to x.

Once the adaptive weights pertaining to the test point x are determined using random forests, a weighted least square (WLS) is performed on equation 1 using the weights. Note that for a new-point x, weights are re-estimated before estimating equation 1. This process is carried out using the GRF package in R.[15] As the treatment occurs at the state level, cluster random sampling is applied at the state level to create a bootstrap sample for each tree.[16]

An important point to note is that the construction of each causal tree is based on "sub-sampling" and "honesty". The sub-sampling criterion is such that a random sub-sample of size s is drawn from the data to construct the tree. Furthermore, the sub-sample is divided into two halves $\mathcal{S}_1$ and $\mathcal{S}_2$. Sample $\mathcal{S}_2$ is used to grow the tree (train the model), while leaf-wise responses are estimated using the $\mathcal{S}_1$ sample. This criteria is known as honesty. This process is repeated for B number of trees to form the causal forest.

The causal forest framework is illustrated in the figure presented below for clarity.

1. Estimate $e(X_i)$ and $m(X_i)$ using the random forest (or any suitable ML method) using cross-fitting.

2. Build B number of causal trees using the clustered random sampling applied at the state level to create a bootstrap sample for each tree. Each tree uses "subsampling" and "honesty" criteria.

3. Calculate adaptive weights for all observations. This tells us how similar an observation i is to the test point x in the course of the forest.

[13]Providing details on how gradient based functions are used to create pseudo outcomes at the parental nodes is beyond the scope of the discussion. Readers are directed to the Athey et al. (2019) study for details.

[14]The weights sum up to 1.

[15]The comprehensive discussion of the package can be found in https://grf-labs.github.io/grf/.

[16]For this process, the whole state (cluster) is selected randomly and random sampling is performed within the cluster.

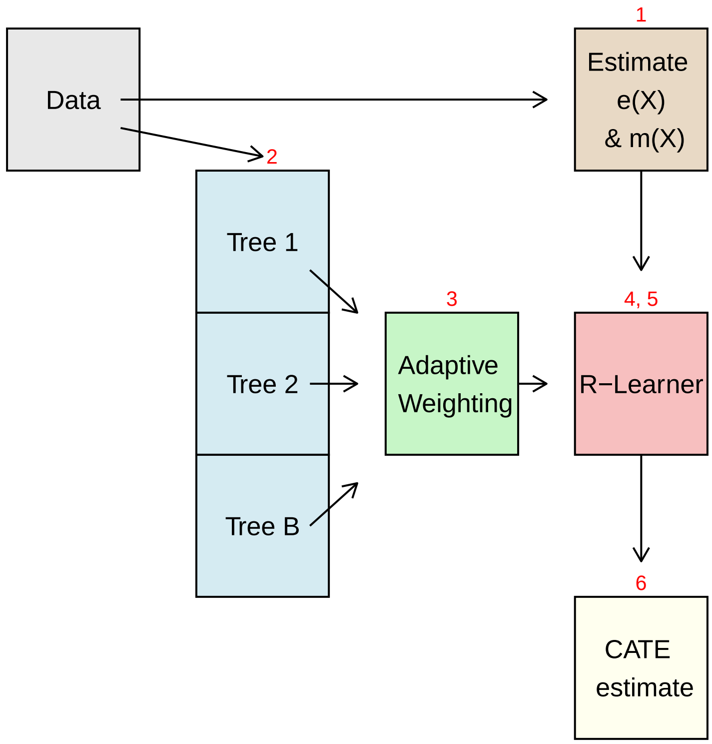


FIGURE 1: An Illustration of the Causal Forest Framework

4. Use estimates on $e(X_i)$ and $m(X_i)$ to get the residual-on-residual components as given in the R-learner framework, given in equation 1.

5. Run the residual-on-residual regression with weights obtained from adaptive weighting (Step 3).

6. Get the estimate on $\tau(X_i)$, which is the Conditional Average Treatment Effect estimate.

Investigating heterogeneity using Rank-Weighted Average Treatment Effects (RATE). To investigate whether the treatment effects vary across the cotton suitability measure, we use RATE metrics as developed in Yadlowsky et al. (2021). The motivation behind RATE is to fit a heterogeneous treatment effect model based on a score measure to provide a "prioritization rule" that can distinguish units with the most treatment benefit. The priority score, $S(.)$, is provided by the user and can include CATE estimates (learned separately), baseline risk measure, or other baseline characteristics (i.e., cotton suitability).

While the utilization of RATE in the context of this study slightly differs from the motivational viewpoint as discussed in Yadlowsky et al. (2021), it aligns effectively with assessing heterogeneity in ACA-Medicaid expansion reform. Decision-makers frequently weigh intervention benefits against costs when designing final policies. Prioritizing individuals with greater treatment benefits, such as drugs for medical treatment, could conceptually streamline policy design. Conversely, similar rationale may not translate perfectly when exploring heterogeneous effects in the context of this study. Rather, it is essential to focus on areas with lower intervention benefit when developing a health care reform aimed at universalization.

RATE metric uses the Targeting Operator Characteristics (TOC) and area under the TOC (AUTOC) to characterize heterogeneity. TOC is defined as:

$$TOC(q) = E[Y_i(1) - Y_i(0)|S(X_i) > F^{-1}_{S(X_i)}(1-q)] - E[Y_i(1) - Y_i(0)] \tag{2}$$

In other words, $TOC(q)$ for $0 \leq q \leq 1$ is defined as the difference in ATE among units above the q^{th} percentile of $S(X_i)$ and the overall ATE. In the presence of significant heterogeneity across the priority score, $TOC(q)$ is significantly higher in magnitude for the lower values of q, while approaching 0 as q gets larger. $TOC(q = 1)$ is simply 0. One measure to summarize the TOC curve is to calculate area under the curve. Formally, RATE is defined as the area under the TOC curve (AUTOC).

In cases when $S(X_i)$ needs to be learned, for example when $S(X_i) = \hat{\tau}(X_c)$ (CATE), the training set is used for the estimation of $\hat{\tau}(X_i)$ while RATE evaluation is performed in the evaluation set. We explore heterogeneity across four prioritization scores: *i*) CATE, *ii*) the baseline risk measure (uninsured rate in 2013), *iii*) a constructed risk measure (that trains a random forest model in 2014 using the expansion units and fits the trained model on non-expansion units), and *iv*) the cotton suitability measure.

Obtaining ATE estimate from CATE. The estimate for ATE is obtained by summarizing CATE estimates using the Augmented Inverse Probability Weighted (AIPW) estimator given as:

$$\begin{aligned}\tau_{AIPW} &= \frac{1}{n}\sum_{i=1}^{n}\left(\mu(X_i,\ 1) - \mu(X_i,\ 0) + W_i.\frac{Y_i - \mu(X_i,\ 1)}{e(X_i)} - (1-W_i).\frac{Y_i - \mu(X_i,\ 1)}{1-e(X_i)}\right) \\ &= \frac{1}{n}\sum_{i=1}^{n}\left(\tau(X_i) + W_i.\frac{Y_i - \mu(X_i,\ 1)}{e(X_i)} - (1-W_i).\frac{Y_i - \mu(X_i,\ 1)}{1-e(X_i)}\right) \\ &= \frac{1}{n}\Gamma_i\end{aligned} \tag{3}$$

where, $\mu(X_i,\ W_i)$ represents the conditional means at each treatment arm, $\mu(X_i,\ W_i) = E(Y_i|X_i = x, W_i = w)$ for $W_i = \{0,\ 1\}$. A plug-in approach is used to obtain an estimate for τ_{AIPW}, with $\hat{\tau}(x)$ estimated using CF. The nuisance parameters $e(X_i)$ and $\mu(X_i,\ W_i)$ are both estimated using random forests subject to cross-fitting. A well-known property of AIPW estimator is double robustness. This property states that the estimator is consistent if either the estimated propensity score $\hat{e}(X)$ or outcome regression $\hat{\mu}(X)$ is consistent.

4.2 Event Study Methods

Next, we investigate the differential gap in insurance outcomes and federal Medicaid-CHIP transfer funds among Southerners by the intensity of slavery measure following the health reform using the specification given below.

$$\begin{aligned} Y_{ast} = \alpha + \sum_{k=-4}^{-2} \gamma_k \times enslaved1860_{as} \times I(t = 2014 + k) + \\ \sum_{k=0}^{4} \gamma_k \times enslaved1860_{as} \times I(t = 2014 + k) + \\ \sigma_a + \phi_t + \epsilon_{ast} \end{aligned} \tag{4}$$

where, Y_{ast} measures the share of uninsured individuals, the federal Medicaid-CHIP transfers per capita, and the proportion with Medicaid coverage in an area demarcation a (county in SAHIE and PUMA in ACS data), within state s, and in year t. $enslaved1860_{as}$ denotes the proportion enslaved in 1860 at area a. The specification interacts the proportion enslaved in 1860 with an indicator $I(t = 2014 + k)$ that marks the year or years before and after the omitted year category 2013, which is the year prior to implementation of ACA. σ_a and ϕ_t represent the area and year fixed effects, respectively. Specification 4 is estimated for both the expansion and non-expansion states separately and the standard errors are clustered at the state level.

The coefficient of interest is γ_k, which traces the evolution of outcomes by the slavery measure before and after the year prior to the reform; i.e., $t \in \{2010,\ 2011,\ 2012,\ 2014,\ 2015,\ 2016,\ 2017,\ 2018\}$ compared to 2013. The number of observations in SAHIE and ACS samples at the area-year cell is used as weights when estimating the specification given by equation 4. The county-level uninsured rates are obtained from SAHIE, while Medicaid coverage and uninsured rates across race groups for White and Black Southerners come from ACS, aggregated at PUMA level.

To assert that the entrenched institution of slavery hindered the effectiveness of the Affordable Care Act (ACA), one must presuppose that if the degree of slavery had been less in areas highly dependent on slavery, the improvements in insurance outcomes related to the ACA would have mirrored those seen in areas with lower reliance on slavery. This is a strong assumption as slavery intensity itself might be associated with third factors, which may affect the implementation of ACA. One approach is to utilize high-dimensional features to control for relevant variables in specification 4. Following the "post-double-selection" method in Belloni et al. (2014), I use LASSO to predict the proportion enslaved in the first step and ΔY (change in uninsured rate between 2013 and 2014) in the second step. The union of the set of variables that are not dropped in the two variable selection steps are linearly controlled for in specification 4 by interacting the selected variables with the post-policy indicator.

Additionally, to address some concerns of spurious relationship, I instrument the proportion enslaved in 1860 using the following county-level variables: i) cotton suitability measure, ii) malaria stability index, *iii*) average precipitation and temperature in the 1990s. The IV technique seeks to utilize only the exogenous variation that is in the data by sacrificing predictive accuracy. Typically, the standard IV method performs in-sample fitting and the fitted values are used in the second step. This increases the risk of overfitting, which biases the IV estimate towards OLS (Mullainathan and Spiess, 2017). Moreover, a researcher uses an ad-hoc approach to introduce the instrument in the first stage (e.g., linearly). Viewing the first stage as a prediction task in lieu of Mullainathan and Spiess (2017), I use random forest to generate predictions of the proportion enslaved in 1860 by using the aforementioned multiple instruments.

Several studies, albeit within a standard instrumental variable (IV) framework, have used the cotton suitability measure as an instrument for slavery (Acharya et al., 2016; Williams, 2017; Mazumder, 2021). In summary, the argument in favor of cotton suitability includes the following: *i*) cotton suitability was determined prior to slavery, *ii*) it satisfies the monotonicity requirement, suggesting that areas more suitable for cotton farming should not reduce slavery dependency, *iii*) slavery intensity is strongly correlated with cotton suitability, which can be tested using available data, and *iv*) it must satisfy the exclusion restriction, meaning that it affects the outcome only through its impact on slavery and not through any other channels.[17] Besides cotton suitability index, I include the malaria stability index as a potential instrument to predict diffusion of slavery building on Esposito (2022).[18] Moreover, long-run temperature and precipitation are used as additional instruments in a multiple instrument framework to explain variation in slavery (Lagerlöf, 2005). Following the prediction in the first stage, the second stage uses $\widehat{enslaved}1860$ (predicted values) in the specification highlighted in equation 4 instead of $enslaved1860$.

4.3 Using the counterfactual of the counties in the expansion states for identification

The enforcement of Medicaid expansion through the Affordable Care Act (ACA), as originally proposed, was deemed unconstitutional by the U.S. Supreme Court. Consequently, Medicaid expansion under the ACA is strictly voluntary for states. Unlike other provisions of the ACA, such as subsidies from exchange market, which can be accessed at the federal level regardless of state actions, Medicaid expansion requires direct state initiative. Therefore, states retain maximum control over Medicaid expansion, potentially driving the historical influence of slavery on the efficacy of such expansion. How do we isolate the "Medicaid-effects" from other health reforms associated with the ACA?

A major challenge in this analysis (and in general) is the lack of access to counterfactual for counties within the expansion states in the absence of Medicaid expansion to evaluate the potential

[17] A direct test of the exclusion restriction is not available. However, past studies provide an indirect test by focusing on the relationship between cotton suitability and the outcome in non-Southern region.

[18] Following the introduction of malaria during colonization and the subsequent increased demand for a workforce resistant to the disease in malaria-infested areas, the author offers empirical evidence suggesting that slavery was prevalent in regions with higher malaria infestation in America. Furthermore, the interaction between malaria stability and soil suitability for cotton increases the intensity of slavery.

impact of slavery on ACA's Medicaid expansion. To address this, we generate a counterfactual for counties within the expansion states under the assumption that the uninsured rates would evolve similarly to their counterparts (counties with similar characteristics but in the non-expansion states) in the absence of Medicaid expansion. A weaker assumption to this is used in difference-in-differences studies examining the impacts of ACA Medicaid expansion on outcomes, which states that, on average, outcomes across the expansion and non-expansion states would trend similarly in absence of the expansion (Frean et al., 2017; Kaestner et al., 2017; Miller and Wherry, 2019; Peng et al., 2020; Miller et al., 2021). By comparing outcomes between expansion and the counterfactual expansion units (hypothetical expansion counties without expansion), we can assess whether differences vary on average with the intensity of slavery. However, another concern is that areas with a high proportion of enslaved populations in 1860 differ significantly from areas with low slavery intensity in both historical and contemporary factors. This requires a careful consideration of these differences to isolate the influence of slavery on the efficacy of Medicaid expansion under the ACA.

The determinants of concentration of slavery across the Southern landscape in 1860 are well-known. Historical studies have highlighted that American slavery in the 1800s fueled the cotton boom (Ransom and Sutch, 2001).[19] As previously mentioned, a handful of studies have used the cotton suitability measure as an instrument for slavery. In a slightly different context, Esposito (2022) provides empirical evidence that the malaria stability index is a robust determinant of slavery. Similarly, Lagerlöf (2005) shows that slavery is positively correlated with temperature and precipitation, while it is negatively correlated with elevation.[20] Given this understanding of the determinants of slavery, we intend to pair counties within state with similar predicted values for the proportion enslaved but across high and low slavery intensity groups. The high vs. low slavery intensity groups are based on the median value of the proportion enslaved among counties within a state. The following steps describe the matching algorithm used to investigate the influence of slavery on the efficacy of Medicaid expansion in more detail.

a. Divide high vs. low enslaved groups within each Southern state based on the median value of the proportion enslaved across counties.

b. Purge the variation in Y (uninsured rate) due to reforms other than Medicaid expansion by using the counterfactual expansion states (without expansion). In the equation below $\ddot{Y}_{it}$ depicts the variation in uninsured rate obtained after puring out the counterfactual outcome.

$$\ddot{Y}_{it} = Y_{it} - Y_{it}^{cf} \ for \ t \in \{2010,\ 2011,\ ...,\ 2018\} \tag{5}$$

[19] It is estimated that one million enslaved people were forced to migrate from the upper South to the deeper South to fuel cotton production (Johnson, 2009).

[20] These variables are also the drivers of malaria suitability index.

where,

$$
\begin{aligned}
Y_{it}^{cf} &= \hat{Y}_{i2013} + \Delta\hat{Y}_{i(t-2013)} \\
\hat{Y}_{i2013} &= g(X_i,\ H_i) \\
\Delta\hat{Y}_{i(t-2013)} &= h(X_i,\ H_i)
\end{aligned} \tag{6}
$$

Equation 6 depicts the construction of counterfactual outcomes. It uses the predicted values of uninsured rate in 2013, the base year, summed with the predicted value of the change in uninsured rate in expansion states between years t and 2013 in absence of the ACA. $\hat{Y}_{i2013}$ (line 3 in the equation) is modeled using the boosted regression forest with 10,000 trees. $\Delta\hat{Y}_{i(t-2013)}$ is also trained using the boosted regression forest but using the training sample of non-expansion states. The trained model is then used to cast prediction for the counties in the expansion states. This approach utilizes the assumption that uninsured rates in counties within the expansion states would have trended similar to their counterparts (counties with similar characteristics but in non-expansion states) in absence of the expansion. Here, X_i denotes the contemporary features prior to ACA used in the model, while H_i represents a vector of historical variables.[21]

c. Use the determinants of slavery to train the boosted regression forest model. The conditional expectation of the proportion enslaved in 1860 takes the form:

$$
\begin{aligned}
E(enslaved_i|X_i) = f(&cotton_i,\ malaria_i,\ avg.precip_i,\ avg.temp_i, \\
&latitude_i,\ longitude_i,\ elevation_i,\ ruggedness_i)
\end{aligned} \tag{7}
$$

where, $cotton_i$ measures the cotton suitability index in county i, $malaria$ refers to the malaria stability index, $avg.temp$ and $avg.precip$ are the long-term measures of average temperature and precipitation, while the geographic variables (latitude, longitude, elevation, and land ruggedness) pertain to the county $i's$ centroid. The trained model is used to predict the values of proportion enslaved, which are based on the out-of-bag observations.

[21] The contemporary variables include the infant mortality measure averaged between the years 2010-2013, the proportion of Whites and Blacks, percapita income, poverty rate, household median income, unemployment rate, the percent of people over 25 years of age with high school and college degree all pertaining to the year 2010. Additionally, household income for the White household at age 35 is for the year 2014 and is extracted from the Opportunity Atlas. The historical variables include the proportion of free Blacks, land inequality measure, the proportion of small farms, farm value per capita, the total count of Whites all measured in the year 1860, as well as measures of crop production including the fraction of cotton, tobacco, sugar, and rice production, and Hill Burton Fund expenses.

d. Match each county in the high enslaved group with a county in the low enslaved group based on the closest predicted values of the enslaved population. For each county i in the high slavery dependent group within a given state, the suitable counterpart $\tilde{i}$ in the low slavery dependent group is found such that:

$\tilde{i} = \underbrace{min}_{i\prime}(|\widehat{enslaved}_i - \widehat{enslaved}_{i\prime}|) \; for \; i\prime \in \{i\prime_1, \; i\prime_2, \; \ldots, i\prime_N\}$

where $\widehat{enslaved}_i$ and $\widehat{enslaved}_{i\prime}$ are the predicted enslaved values for the county i and $i\prime$, respectively, and N is the number of counties in a state. As such, a given county in the low enslaved group may be paired with one or more counties in the high enslaved group.

e. Next, we take the difference in uninsured rates across each matched pair: $(\Delta Y_{it} = \ddot{Y}_{it} - \ddot{Y}_{\tilde{i}t})$.

f. Run the following regression for the expansion and non-expansion states for each year separately, $years \in \{2010, \; 2011, \; ..2018\}$.

$$\Delta Y_i = \alpha + \epsilon_i. \tag{8}$$

α is the intercept, and ϵ is the error term. The estimate and the standard error on the intercept term allow us to interpret whether the average difference in uninsured rates among the matched pairs is positive and statistically different from zero. If $\hat{\alpha} > 0$, it would signal a higher uninsured rate in counties more dependent on slavery, on average, compared to the matched counterpart in low slavery-dependent group (i.e., counties with similar predicted value for the proportion enslaved but with actual low dependency on slavery) in the years following the ACA.

5 Results

5.1 Heterogeneous treatment effects of Medicaid expansion (CATE estimates)

I use county level data from SAHIE merged with other datasets as discussed in section 3 to explore heterogeneity of ACA-Medicaid expansion policy in South. To build causal forests, the analysis uses the cross-sectional setting of the data. This means that a single year, as a subset of the main dataframe (e.g., year 2014) is used, while identifying $\hat{\tau}(x)$ (CATE estimates). Focusing on 2014 enables the examination of the short-run effects and may offer higher power in detecting heterogeneity due to initial barriers that can be more pronounced in slavery-dependent areas, including administrative and bureaucratic hurdles, unrealized benefits of the reform, and information gaps between the policymakers and potential beneficiaries.

As previously mentioned in Section 4.1, the identification is governed by the unconfoundedness assumption. Specifically, in the context of CF, it means that within the same neighborhood of the target sample x determined by the covariates, treatment allocation is as good as random and τ is constant. The covariates used to place splits and for the purpose of estimating nuisance components are summarized in Table 1 in the Appendix. The method first performs orthogonalization of the outcome and the treatment to get the residuals or the centered outcomes using random forest run on W and Y. Next, the forest is run on the residuals.

Figure B2 presents the VIP (very important variable plot) for W (treatment) and Y (uninsured rates in 2014), respectively.The figure shows that the majority of splits while building the regression forest for W come from geographical, climate, and Whites' votes for Obama in the 2008 presidential election. The majority of splits in the Y variable (uninsured rate in 2014) are determined by the uninsured rate in 2013.

I begin with the discussion regarding the estimates of ATE as shown in Table 1 using various approaches, including the CF. The outcome variable is the uninsured rates among people below 138% of FPL in 2014 (or the first difference, i.e. Δ uninsured rate between 2014 and 2013, in some cases). Column 1 presents estimate from the "naive estimator" (i.e., simple difference in means between the treatment and control groups), column 2 presents the ATE estimate following the difference-in-differences framework using the first difference (ΔY_c, change in uninsured rate between 2014 and 2013), column 3 summarizes the CATE estimates from the CF using the AIPW approach as discussed in Section 4.1, and column 4 does the same but for the outcome constructed using the first difference before and after the policy (Δ uninsured rates between 2014 and 2013). Additionally, columns 5 and 6 summarize CATE estimates obtained from the CF framework but when the response variable is the uninsured rate in 2013 and the first difference in the outcome prior to the policy.

The ATE estimate based on the naive estimator, as shown in column 1, (incorrectly) suggests that on average the uninsured rate decreased by 15.42 percentage points due to the Medicaid expansion reform. The assumption governing this estimator presupposes that the treatment is randomly assigned, a presumption which may be flawed due to various factors. For instance, the baseline insurance outcomes in treated areas may systematically differ compared to non-expansion areas. The DD estimate accounts for the time invariant unobserved heterogeneity by utilizing the panel nature of data and is used as the benchmark. The ATE estimate based on the DD framework is lower than the naive estimate, suggesting that the reform lowered the uninsured rate by 11.88 percentage points. The summary of CATE estimates, or $\hat{\tau}_{AIPW}$, is similar in magnitude to the DD estimate but lower than the naive estimate and suggests that on average ACA-Medicaid expansion reduced the uninsured rate by 12.52 percentage points. In column 4, the ATE estimate when using the first differenced outcome variable is also similar in magnitude to the DD estimate. Finally, the ATE estimates summarized using CF approach but pre-policy outcome in columns 5 and 6 are close to zero and statistically insignificant. This lends evidence in support of the validity regarding the ATE estimate from the CF method.

Figure B5 demonstrates the synopsis of balance between the covariates across treatment and control units. The unadjusted absolute standardized mean difference is widespread. Once units are inversely weighted using the propensity score, the adjusted difference in mean hovers close to zero. This indicates that propensity scores are critical in improving comparability between the treatment and control units.

How do these estimates compare to other ATE estimates pertaining to ACA-Medicaid expansion in the literature? Although a direct one-to-one comparison is not feasible due to the study's primary focus on the American South, it provides valuable insights that contribute to the broader understanding of the effects of ACA-Medicaid expansion, complementing existing estimates in the literature. The magnitude of the preferred ATE estimate from CF (column 3) is in line with or even higher than compared to the findings reported in the literature that pertain to the whole of America. For example, using data from the National Health Interview Survey (NHIS), Miller and Wherry (2019) find that low-income respondents are 7 percentage points less likely to be uninsured following the reform year, while the ATE magnitude increases to 12 percentage points during the fourth year. Similarly, Courtemanche et al. (2017) indicate that ACA is predicted to increase insurance coverage among people below 138% of FPL by 10.3 percentage points.

Before moving on to the heterogeneous treatment effects, we provide a brief discussion of the role of important variables in the construction of the causal forest evaluating the impacts of Medicaid expansion. The uninsured rate in 2013 explains the highest number of splits in the course of the forest, followed by geographical variables including longitude and latitude. Additionally, the proportion of free Blacks in 1860 and malaria stability index constitute over 5 percent of splits, while the proportion of White votes for Obama in the 2008 presidential election and the cotton suitability measure explains just below 5 percent of splits. It is interesting to note that the forest itself identifies some critical variables of interest for the study, including the proportion of free Blacks in 1860, White Obama votes, and the cotton suitability measure.

Figure B4, Panel A, plots the histogram of CATE estimates. The CATE estimates are negative and the histogram shows presence of a left tail. As an exercise to examine the importance of orthogonalization before running CF, Panel B presents CATE estimates from orthogonalized versus non-orthogonalized CF models.[22] Although CATE estimates from two approaches are positively correlated, the magnitudes of the estimates in the case of non-orthogonalization are strictly higher compared to the orthogonalized CATE estimates. This suggests that failing to account for covariates that are systematically linked to both treatment allocation and outcome can lead to an overestimation of treatment effects.

Next, we turn to the evaluation of whether the treatment effects reflect heterogeneity based on the priority scores. The sub-figures in Figure 4 plot the TOC curves after evaluating heterogeneity following the RATE metric as discussed in Section 4.1. Panel A uses CATE estimates ($\hat{\tau}(x)$) as the priority score $S(.)$, Panel B uses the baseline uninsured rate in 2013 (a year prior to the policy), Panel C shows heterogeneity based on the cotton suitability measure, and Panel D runs a falsification-type exercise using the CF trained on the response variable prior to the ACA, the uninsured rate in 2013.

Panel A documents strong heterogeneity by the magnitude of estimated CATE – the reduction

[22] To obtain CATE estimates from the non-orthogonalized approach, I center the outcome using trivial means, $\hat{w} = \frac{1}{n}\sum_{i=1}^{n} W_c$ and $\hat{y} = \frac{1}{n}\sum_{i=1}^{n} Y_c$. Next, I run CF using the trivial format of the centered variables.

in uninsured rate for units that benefited most from ACA-Medicaid reform, the top 10% of the counties, experienced reductions in uninsured rate close to 13 percentage points more than the overall ATE estimate. The AUTOC measure, summarizing the TOC curve, is negative and statistically significant at the 10 percent level. Panel B shows that areas with a high baseline uninsured rate experienced greater improvements in the insurance outcome. However, no segment of the TOC curve is statistically significant.

Panel C shows the focal finding aligned with the research objective of this study. The TOC curve provides evidence of heterogeneous CATE estimates by the cotton suitability measure. Counties with unyielding cotton suitability measure (low cotton suitability) experienced more pronounced reductions in the uninsured rate among individuals below 138% of FPL after the implementation of the ACA-Medicaid expansion. The AUTOC measure summarizes the presence of heterogeneity based on the cotton suitability index by estimating the area under the TOC curve. The 90% confidence interval of the AUTOC estimate is given as $[-0.0635, -2.5385]$.

To investigate whether the pattern depicted in Panel C is driven by the pre-existing relationship between the cotton suitability measure and uninsured rate, Panel D presents the TOC curve from the CF model using the uninsured rate in 2013 as the response variable. The TOC curve is flat and statistically insignificant. This indicates that while uninsured rate did not vary across the cotton suitability measure between the expansion and non-expansion states in the year prior to the reform, areas with lower cotton suitability experienced disproportionately higher benefits of ACA during the implementation year.

5.2 Differential gap in uninsured rates by the slavery measure

Figure 5 presents estimates on $\hat{\gamma}$ after estimating specification 4. The dependent variable used in Panels A and C is the uninsured rate among people within the indicated income category (obtained from SAHIE), while Panels B and D use Medicaid transfers per capita. Panels A and B pertain to the non-expansion states, while C and D pertain to expansion states.

Panels A and B show no differential gaps in uninsured rates across the reported income categories and Medicaid transfers by slavery within non-expansion states. The event study estimates are close to zero and quite precisely estimated. On the other hand, Panel C indicates that the gap in uninsured rates remained uniform across counties with different levels of slavery prior to the Medicaid expansion reform. After the reform, there was a disproportionate decline in the uninsured rate, with areas characterized by greater dependence on slavery experiencing relatively smaller reductions. This pattern is concentrated among people in the low income groups, mainly individuals below 138% of FPL. For instance, a percentage point increase in the proportion enslaved in 1860 is associated with a relative increase in uninsured gap among the lowest income category by around 0.15 percentage points in 2014 and 2015 (compared to the gap in 2013). In other words, an increase in the proportion enslaved by a standard deviation is associated with relative increase in uninsured rate by 3.15 percentage points. This aligns with a pattern of relatively lower Medicaid funding allocation in historically slavery-dependent areas following the reform as shown in Panel D, while no discernible relative differences in funding are observed in years prior to the reform .

Are poor White Southerners in slavery dependent areas forgoing the benefits of the ACA? To evaluate this, we use the American Community Survey (ACS) sample consisting of individuals aged 26 and above with a high school education or below. We then utilize specification 4 to examine outcomes independently for White and Black Southerners in expansion and non-expansion states. The findings are presented in Figures 6 and 7 for the expansion and non-expansion states, respectively. Panels A, B and C, D pertain to Black and White Southerners.

Figure 6, Panel A, shows that the relative difference in Medicaid coverage among White Southerners by the dependency on slavery (compared to the omitted category 2013) is precisely estimated at zero prior to the ACA implementation. Following the reform, Medicaid coverage improved disproportionately in low slavery-dependent areas until 2016. The disparity in coverage based on reliance on slavery diminishes in 2017, coinciding with the implementation of Medicaid expansion in Louisiana. The pattern of the emergence in relative gap by slavery is mirrored when using uninsured rate among White Southerners as the outcome (Panel B). The improvement in insurance outcome among White Southerners is more pronounced in areas with lower dependency on slavery. Conversely, the discrepancy in insurance outcomes among Black Southerners remains consistent across slavery measures until 2016. In fact, areas with a high historical prevalence of slavery demonstrate greater success in reducing the uninsured rate following Louisiana's Medicaid expansion in the mid-2016.

When shifting focus to the non-expansion states in Figure 7, Panel A demonstrates that White Southerners' Medicaid coverage did not change systematically based on the dependency on slavery. The event study coefficients are close to zero in the pre-ACA years, while the coefficients do not exhibit a break in the trend following the ACA implementation. In contrast, Panel B documents that the uninsured rate among White Southerners improved at a lower rate in areas more dependent on slavery following the reform. While this informs that benefits of ACA was suppressed among poor White Southerners in high-slavery dependent areas in non-expansion states, such is not the case among Black Southerners. Findings in Panel C indicate that Medicaid coverage improved in high slavery dependent areas in 2015 and 2016, with gaps soon closing to zero in successive years. Due to some evidence of pre-existing trends, no conclusive findings can be drawn from panel D.

In summary, the event study findings indicate that the benefits of ACA implementation among the White race group were disproportionately pronounced in areas with low dependence on slavery. Specifically, White Southerners in high slavery-dependent areas in expansion states experienced lower improvements in Medicaid coverage and uninsured rates. Likewise, improvements in insurance outcomes among White Southerners in non-expansion states occurred at a slower rate in areas with higher dependency on slavery. These disparities underscore the complex interplay between historical context, policy implementation, and healthcare access, consistent with the conceptual framework established in Section 2.

To further investigate whether the findings are robust to controls for historical as well as pre-treatment contemporaneous variables, I re-estimate specification 4 after including the selected variables from double-step post-LASSO following Belloni et al. (2014). The selected variables are interacted with the post-policy indicator to avoid multicolleniarity and to allow for the controls to affect the outcome differently following the reform.[23] The findings depicted in Figure B6, focusing solely on the uninsured rate among individuals below the 138% of the Federal Poverty Level (FPL) (panels A and C) and per capita Medicaid transfers (Panels B and D), exhibit thematic similarity to the primary findings illustrated in Figure 5.

Next, Figure B7 provide estimates after instrumenting the proportion enslaved in 1860 by using the cotton suitability, malaria stability, and long-run climate variables as discussed in Section 4.2. The uninsured rate pertains to individuals with income below the 138% of FPL. The observed patterns in the IV estimates are similar to the main findings presented in Figure 5.

5.3 The influence of slavery on Medicaid expansion – Using the counterfactual

As previously mentioned, the influence of slavery on the efficacy of ACA can differ across expansion vs. non-expansion states primarily given states' control over the Medicaid program. To evaluate the influence of slavery on Medicaid expansion, we follow the steps as defined in the matching algorithm discussed in Section 4.3. Briefly, each county in the high enslaved group is matched with a county in the low enslaved group such that the counterpart county minimizes the absolute difference in predicted enslaved values in 1860 across the matched pairs. Next, we evaluate whether, on average, the difference in the uninsured rate through the ACA's Medicaid expansion between high vs. low slavery-dependent groups is positive and statistically different from zero.

The findings from this approach are presented in Figure 8. Panels A and B show the distribution of the predicted values of the proportion enslaved in 1860 across non-expansion and expansion states, respectively. The distribution of the predicted enslaved values for counties in the high enslaved group is towards the right compared to those pertaining to the low enslaved group for both the non-expansion and expansion states. However, a notable portion of overlap exists in the predicted values of the proportion enslaved across the high and low slavery intensity regions.

Panel C of Figure 8 shows the trend in uninsured rate across three categories. The first two, for the expansion and non-expansion states are self-explanatory. The uninsured rates dropped following the reform across both the expansion and non-expansion states, while the drop is a lot sharper in the expansion states. The third category is given by the counterfactual scenario for expansion states (i.e., the hypothetical expansion states without expansion) denoted by the blue squared markers. The trend in the uninsured rate for the counterfactual mirrors that of the expansion states prior to the reform and follows a trajectory similar to non-expansion states post reform. This is based on the governing assumption that the uninsured rate in counties in the expansion

[23] The list of variables selected from the double step post LASSO include: 1) Whites' household income at age 35; 2) poverty rate in 2010, 3) unemployment rate in 2010, 4) household median income in 2010, 5) percent with four years of college in 2010, 6) rural-urban code in 2013, 7) county population in 2010, 8) mortality rate (White between 2010 and 2013), 9) uninsured rate in 2013, 10) White-Black incarceration ratio in 2014, 11) Blacks' (Whites') wage in 1940, 12) pm 2.5 measure in 2010, 13) land inequality measure in 1860, 14) farm value in 1880, 15) acres of improved land in 1860, and 16) rail and water access in 1860.

states would trend similar to their counterparts (counties with similar characteristics but in non-expansion states) in the absence of expansion. This implies that the gap between the expansion states and their counterfactual counterparts highlight the impact of the Medicaid expansion on the uninsured rates. As depicted in Panel C, this differential provides a clear measure of how Medicaid expansion contributed to reducing the uninsured rate in expansion states compared to what would have been observed without the expansion.

Panel D depicts the difference in uninsured rates, adjusted for the counterfactual outcome, between high and low slavery-dependent areas within the expansion states. Specifically, it plots the estimate on the intercept term (α) in equation 8. The estimates hover around zero in the years preceding the expansion year, 2014. Following the Medicaid expansion in 2014, the estimates increase in magnitude, peaking in 2016. In 2016, the reduction in uninsured rate was, on average, a percentage point higher in slavery-dependent areas compared to those with lower dependence on slavery. The findings from this approach yet again suggests that the ACA (Medicaid expansion) provided disproportionate benefits to counties less dependent on slavery relative to those with high dependency on slavery. In summary, counties with a history of high slavery dependence did not experience as significant a reduction in uninsured rates as counties with low slavery dependence.

A fundamental challenge in this approach, as with any causal inference method, is absence of ground truth to determine how the outcome might have evolved had the expansion states not expanded Medicaid. Until now, the counterfactual for the Medicaid expansion states has been formed using all Southern states that did not expand Medicaid until 2018.[24] However, the appropriateness of including all non-expansion states in the counterfactual is debatable. Deep Southern states may differ significantly from expansion states in variables that predict uninsured rates. To address this concern, we generate the counterfactual of the expansion states (in the absence of Medicaid expansion) using only the Southern states bordering the expansion states including TN, MS, TX, VA, and LA (LA, only for years before the expansion year in 2016). By focusing on bordering Southern states, the revised counterfactual aims to provide a more accurate comparison group, reflecting conditions and characteristics more closely aligned to those of the expansion states. We then replicate the analysis with this refined counterfactual group. The findings, as shown in Figure B8 in the Appendix, are consistent with those presented in Figure 8, thereby reinforcing the robustness of our original conclusions.

Finally, using the outcome adjusted for the counterfactual, $\ddot{Y}_{it}$ in equation 5, we estimate the event-study specification as shown in equation 4 for the expansion states. The findings, as shown in Figures B9 and B10 in the Appendix which use all the non-expansion states and bordering non-expansion states to obtain the counterfactual scenario respectively, are consistent to the findings shown in Figure 5 (Panel C for income group less than 138% of FPL).

[24]This includes VA, SC, NC, GA, FL, AL, MS, TX, and TN.

6 Mechanisms

Mechanization

Following the established connection between mechanization and the reduced need for a paternalistic structure supporting sharecropping (Alston and Ferrie, 1993; Day, 1967), I evaluate the differential effects of ACA expansion based on the level of slavery dependency in areas that attained high versus low rates of partial mechanization. To proxy for the rate of mechanization, I use the introduction of tractors (per acre of a county) between the 1930s and 1940s.[25]

Two pathways can tie in mechanization and ACA implementation through the legacy of slavery. First, given that mechanization helped uproot the culture of paternalism in the American South as maintaining sharecroppers throughout the year became uneconomic, areas that mechanized early should be relatively less opposed to redistributive programs. This is because the dismantaling of the paternalistic system early on in these areas diminished economic incentives to oppose the welfare state policies. Second, building on the argument posed in Acharya et al. (2016), tactics promoting labor control through racial hostility should decrease in areas that mechanized earlier due to less reliance on Black labor. Both pathways predict that implementation of the ACA should be more effective in slavery-dependent areas that mechanized earlier, compared to areas with similar levels of dependency but later mechanization.

I trace the relationship between historical slavery, mechanization, and ACA implementation using the triple interaction term as presented in Table 2. The coefficient on the interaction between the proportion enslaved in 1860 and post-policy shows the evolution of outcomes based on the slavery measure following ACA. The triple interaction term helps uncover the relationship between slavery and outcomes in high mechanized areas following the reform.

Within the expansion states, in areas with low growth in mechanization between 1930 and 1940, an increase in enslaved proportion by a standard deviation is associated with a relative increase in uninsured rate (for individuals below 138% of FPL, column 1) of 2.99 percentage points (13.79×0.217 (sd)). Conversely, in areas characterized by substantial growth in mechanization during the same period, the impact of a similar increase in the proportion of enslaved individuals results in a relative increase in the uninsured rate of 2.416 percentage points [$(13.79-2.658)\times 0.217$]. Column 2 presents the findings when using overall uninsured rate as the outcome. The coefficient on the triple interaction term is even larger in magnitude and statistically significant at the 1 percent level. Such differential effects by levels of mechanization and slavery measure are not observable within non-expansion states.

Inertia of slavery on present-day political preference and ACA implementation

As previously discussed, the ACA was highly politicized and elicited strong bipartisan preferences. Can the disparity in levels of ACA implementation be explained by current political preferences rooted in the historical prevalence of slavery, or is it driven by more recent elite capture? This

[25] The same variable is used to proxy for mechanization in Acharya et al. (2016) and Hornbeck and Naidu (2014).

section explores these dynamics, focusing on the influence of slavery on the ACA's efficacy through contemporary politics. In this line, we build on Acharya et al. (2016) findings that document the persistent effect of historical slavery in shaping contemporary political outcomes.

We explore the potential pathway of inertia in political preferences stemming from the institution of slavery in two ways. In the first approach we move backwards. We predict the proportion enslaved in 1860 using the current day political outcomes and obtain residuals using a random forest fit. More formally, model is given as the following.

$$enslaved1860_c = f(contemporary\,politics_c,\ U_c) \tag{9}$$

Here, $contemporary; politics_c$ is a vector that includes Trump votes in 2016, White votes for Obama in 2008, and whether a county is Democrat, whereas U_c includes unexplained variation in the proportion enslaved. This backward-looking process decomposes the variation in slavery into two components: ii the predicted values contain the variation in slavery explained by contemporary political measures (explained variation), and iiii the residuals are unexplained by current-day measures (unexplained variation). I incorporate both the explained and unexplained variations of the slavery measure in the event study framework similar to the one portrayed in equation 4.[26]

Figure 9 shows the results from using the decomposed explained and unexplained variations. The event study coefficients for both the explained and unexplained components prior to the policy are close to zero and statistically insignificant. It is intriguing to observe that coefficients for the explained component are positive following the reform, while those pertaining to the unexplained component are negative. This implies that the portion of variation in slavery that aligns with the contemporary political landscape influences the main results.

Next, we utilize the determinants of slavery (i.e., cotton suitability measure, malaria stability, long-run climate variables) to predict White Southerners' vote for Obama in the 2008 presidential election. We then isolate variations in contemporary political outcomes explained by factors determining the intensity of slavery versus other unexplained measures. The model is given as:

$$WhiteObamaVotes_c = f(Z_c,\ V_c) \tag{10}$$

Z_c is a vector consisting of variables that determined slavery dependency as mentioned above. The above model is fit using a random forest. The predicted values encompass variation in contemporary political preferences that are explained by the determinants of slavery, while netting out the more recent changes in the political landscape. Subsequently, I incorporate the interaction between the predicted White Southerners' vote share for Obama and year indicators in equation 4 along with the initial slavery measure. The findings are reported in Figure 9, panel B. The results show that White Southerners' support for Obama, explained using the determinants of slavery, significantly influences the implementation of the ACA. The reduction in the uninsured rate is

[26] The proportion enslaved in 1860 in equation 4 is replaced by the explained variation in slavery. Additionally, the interaction between the unexplained variation and year indicators are incorporated into the same specification.

particularly pronounced in areas with higher predicted White votes for Obama. Once accounting for the contemporary political landscape explained by the determinants of slavery, the coefficient on the slavery measure, although still positive, decreases in magnitude and becomes statistically insignificant at the 10 percent level. This provides firm evidence that the inertia of the institution of slavery, which influences the contemporary political landscape, explains why the ACA implementation is weaker in high slavery-dependent areas.

Additionally, Panel C presents estimates from controlling for the White votes for Obama unexplained by the determinants of slavery (residuals) using specification 4. The estimates show a similar pattern as in Figure 5. This shows that the relationship between the slavery measure and ACA efficacy is unaffected after accounting for the variation in contemporary political preference unexplained by the determinants of slavery.

Racial Resentment

The study uses the measures of racial prejudice as proxies for racial resentment by using data from the Project Implicit, an Implicit Association Test (IAT) aimed at measuring unconscious biases and attitude towards racial groups. We use explicit and implicit measures of prejudice, with the former representing whether an individual prefers European Americans over Blacks and the latter denoting the IAT score defining an association between the concepts of "White" and "good". The individual-level data from Project Implicit are merged with the county-level variables using county codes and are aggregated at the county level.

Figure 10 shows the relationship between the intensity of proportion enslaved in 1860 and racial biases, where the top and bottom panels report Whites' and Blacks' preferences, respectively. Subfigure A indicates that the proportion of Whites preferring European Americans as compared with Blacks increases with the slavery dependency. As shown by the best-fit line, 30 percent of Whites residing in the lowest slavery ventile report explicit bias in favor of European Americans, while close to 40 percent of Whites in the highest slavery ventile prefer European Americans. This pattern is consistent when observing the measure of implicit racial bias, presented by IAT score in panel B. Disproportionately higher portion of Whites in slavery-dependent areas associate "White race" and "good". In contrast, the pattern generated by Blacks' preferences, exhibited in bottom panels, is opposite to Whites' preferences. For instance, Panel D shows that Blacks residing in slavery-dependent region on average have lower IAT score associating "Whites" with "good".

While these results align generally with the findings of Acharya et al. (2016), it is worth noting that their study exclusively relies on explicit measures of racial prejudice. By contrast, our study delves into implicit measures of racial bias. This addition to the narrative of racial resentment suggests that there could be significantly heightened levels of racial prejudice against Blacks at the subconscious level, particularly among Whites residing in areas historically reliant on slavery.

7 Conclusion

Although the passage of the ACA in March 2010 took America several steps closer to the direction of universal healthcare, the reform has been met with turbulent opposition on several grounds. To an extent, reasons behind the opposition coincide with those against the universal healthcare system, which includes exorbitant costs, increased government involvement, inefficiency, and lower quality of health care in favor of an increased access. However, the intensity of opposition towards the reform has mainly been concentrated in the American South. This study argues that the institutional legacy of American slavery in the South has helped shape ACA-related preferences and also affected its efficacy in the southern landscape.

The study provides three main findings. Firstly, in examining the heterogeneous effects of ACA-Medicaid expansion in the American south, the results show that the implementation of the ACA was stronger in areas with a low measure of the cotton suitability index, a variable empirically proven to be a significant determinant of slavery (Acharya et al., 2016; Williams, 2017; Mazumder, 2021). Secondly, although the ACA-related Medicaid expansion led to a reduction in the uninsured rate in the expansion states, the extent of this reduction was disproportionately higher among White Southerners in areas less dependent on slavery. Furthermore, the uninsured rate among White Southerners decreased at a relatively lower rate in slavery-dependent areas, even in non-expansion states following the reform. These patterns were not observed among Black Southerners, as their outcomes did not exhibit similar disparities based on historical slavery. Thirdly, the study presents evidence in favor of potential mechanisms linking the inertia of historical slavery on the implementation of ACA, which suggests that the barriers posed by the institution of slavery are influenced by the current political landscape explained by the determinants of slavery. Furthermore, the impact of slavery on ACA implementation was less pronounced in areas that mechanized at a faster rate compared to those experiencing later mechanization.

While a large body of literature has highlighted the importance of the ACA in improving access to healthcare as well as health outcomes (see Antonisse et al. (2018) for a review), the implementation of the reform varies across the geographical landscape. Ironically, the American South, a region where the marginal benefits of the ACA could be particularly substantial given the poor baseline outcomes such as high uninsured rates and mortality rates, has been resistant to the full integration the ACA's efficient elements, notably the ACA-Medicaid expansion. One crucial factor elucidating the weak implementation of the redistributive health reform in the American South is the deep-rooted legacy of institutional slavery.

References

Aaronson, D. and Mazumder, B. (2011). The impact of rosenwald schools on black achievement. *Journal of Political Economy*, 119(5):821–888.

Acharya, A., Blackwell, M., and Sen, M. (2016). The political legacy of American slavery. *The Journal of Politics*, 78(3):621–641.

Ager, P., Boustan, L., and Eriksson, K. (2021). The intergenerational effects of a large wealth shock: White Southerners after the Civil War. *American Economic Review*, 111(11):3767–94.

Alston, L. J. and Ferrie, J. P. (1985). Labor costs, paternalism, and loyalty in southern agriculture: A constraint on the growth of the welfare state. *The Journal of Economic History*, 45(1):95–117.

Alston, L. J. and Ferrie, J. P. (1993). Paternalism in agricultural labor contracts in the us south: Implications for the growth of the welfare state. *The American economic review*, pages 852–876.

Althoff, L. and Reichardt, H. (2022). Jim Crow and Black economic progress after slavery.

Antonisse, L., Garfield, R., Rudowitz, R., and Artiga, S. (2018). The effects of medicaid expansion under the aca: updated findings from a literature review. *Published March*.

Arias, E., Bastian, B., Xu, J., and Tejada-Vera, B. (2021). National Vital Statistics Reports. *National Vital Statistics Reports*, 70(1).

Atack, J. (2015). Historical Geographic Information Systems (GIS) database of Steamboat-Navigated Rivers During the Nineteenth Century in the United States. https://my.vanderbilt.edu/jeremyatack/data-downloads/.

Atack, J. (2016). Historical Geographic Information Systems (GIS) database of U.S. Railroads for [selected years based on value of .dbf field "InOpBy" or "Exact"]. https://my.vanderbilt.edu/jeremyatack/data-downloads/.

Athey, S., Tibsharani, J., and Wager, S. (2019). Generalized random forests. *The Annals of Statistics*, 47(2):1148–1178.

Belloni, A., Chernozhukov, V., and Hansen, C. (2014). Inference on treatment effects after selection among high-dimensional controls. *Review of Economic Studies*, 81(2):608–650.

Bertocchi, G. and Dimico, A. (2014). Slavery, education, and inequality. *European Economic Review*, 70:197–209.

Bisin, A. and Verdier, T. (2011). The economics of cultural transmission and socialization. In *Handbook of social economics*, volume 1, pages 339–416. Elsevier.

Blalock, H. M. (1967a). *Race and Ethnic Relations*. Pretence-Hall, Inc., New Jersey.

Blalock, H. M. (1967b). *Toward a Theory of Minority-Group Relations*. New York: John Wiley & Sons.

Boyd, R. and Richerson, P. J. (1996). Why culture is common, but cultural evolution is rare. In *Proceedings-British Academy*, volume 88, pages 77–94. Oxford University Press Inc.

Breiman, L., Friedman, J. H., Olshen, R. A., and Stone, C. J. (1984). Classification and regression trees. *CA: Wadsworth International Group*.

Charnysh, V. (2015). Historical legacies of interethnic competition: Anti-Semitism and the EU referendum in Poland. *Comparative Political Studies*, 48(13):1711–1745.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., and Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters: Double/debiased machine learning. *The Econometrics Journal*, 21(1).

Clubb, J. M., Flanigan, W. H., and Zingale, N. H. (2006). Electoral data for counties in the united states: Presidential and congressional races, 1840-1972.[computer file]. icpsr08611-v1. *Ann Arbor, MI: Inter-university Consortium for Political and Social Research (ICPSR)[distributor]. doi*, 10.

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

Currie, J., Voorheis, J., and Walker, R. (2023). What caused racial disparities in particulate exposure to fall? New evidence from the clean air act and satellite-based measures of air quality. *American Economic Review*, 113(1):71–97.

Dawes, D. E. (2016). *150 years of Obamacare*. JHU Press.

Day, J. K. (2014). *The Southern Manifesto: Massive resistance and the fight to preserve segregation*. Univ. Press of Mississippi.

Day, R. H. (1967). The economics of technological change and the demise of the sharecropper. *The American Economic Review*, 57(3):427–449.

Dell, M., Lane, N., and Querubin, P. (2018). The historical state, local collective action, and economic development in Vietnam. *Econometrica*, 86(6):2083–2121.

Di, Q., Kloog, I., Koutrakis, P., Lyapustin, A., Wang, Y., and Schwartz, J. (2016a). Assessing pm2. 5 exposures with high spatiotemporal resolution across the continental united states. *Environmental science & technology*, 50(9):4712–4721.

Di, Q., Kloog, I., Koutrakis, P., Lyapustin, A., Wang, Y., and Schwartz, J. (2016b). Assessing pm2. 5 exposures with high spatiotemporal resolution across the continental united states. *Environmental science & technology*, 50(9):4712–4721.

DuRocher, K. (2011). *Raising racists: The socialization of white children in the Jim Crow South*. University Press of Kentucky.

Esposito, E. (2022). The side effects of immunity: Malaria and african slavery in the united states. *American Economic Journal: Applied Economics*, 14(3):290–328.

Fouda, A. and Paolucci, F. (2017). Path dependence and universal health coverage: The case of Egypt. *Frontiers in Public Health*, 5:325.

Foundation, K. F. (2012). States' positions in the Affordable Care Act case at the Supreme Court. https://www.kff.org/health-reform/state-indicator/state-positions-on-aca-case/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D.

Frean, M., Gruber, J., and Sommers, B. D. (2017). Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act. *Journal of Health Economics*, 53:72–86.

Fuchs, V. R. (2013). How and why US health care differs from that in other OECD countries. *Jama*, 309(1):33–34.

Gilens, M. (1995). Racial attitudes and opposition to welfare. *The Journal of Politics*, 57(4):994–1014.

Giles, M. W. (1977). Percent black and racial hostility: An old assumption reexamined. *Social Science Quarterly*, 58(3):412–417.

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

Haeder, S. F. (2012). Beyond path dependence: Explaining healthcare reform and its consequences. *Policy Studies Journal*, 40:65–86.

Hoehn-Velasco, L. (2018). Explaining declines in us rural mortality, 1910–1933: The role of county health departments. *Explorations in Economic History*, 70:42–72.

Hornbeck, R. and Naidu, S. (2014). When the levee breaks: Black migration and economic development in the American South. *American Economic Review*, 104(3):963–90.

Jacobs, L. R. and Skocpol, T. (2011). Chapter 2 hard-fought legacy: Obama, congressional Democrats, and the Struggle for comprehensive health care Reform. *Reaching for a new deal: ambitious governance, economic meltdown, and polarized politics in Obama's first two years*, page 53.

Jacobson, C. G. (2007). *A Divider, Not a Uniter*. New York: Pearsons Education.

Johnson, W. (2009). *Soul by soul*. Harvard University Press.

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

Key, V. (1984). *Southern Politics in State and Nation*. Knoxville: University of Tennessee Press.

Kinder, D. R. and Sanders, L. M. (1996). *Divided by color: Racial politics and democratic ideals*. University of Chicago Press.

Kiszewski, A., Mellinger, A., Spielman, A., Malaney, P., Sachs, S. E., Sachs, J., et al. (2004). A global index representing the stability of malaria transmission. *American Journal of tropical medicine and hygiene*, 70(5):486–498.

Knowles, E. D., Lowery, B. S., and Schaumberg, R. L. (2010). Racial prejudice predicts opposition to Obama and his health care reform plan. *Journal of Experimental Social Psychology*, 46(2):420–423.

Lagerlöf, N.-P. (2005). Geography, institutions and growth: The United States as a microcosm. *Working paper, author's website*.

Lanford, D. and Quadagno, J. (2016). Implementing Obamacare: the politics of Medicaid expansion under the Affordable Care Act of 2010. *Sociological Perspectives*, 59(3):619–639.

Light, D. W. (2003). Universal health care: Lessons from the British experience. *American journal of public health*, 93(1):25–30.

Mazumder, S. (2021). Old south, new deal: how the legacy of slavery undermined the new deal. *Journal of Historical Political Economy*, 1(3):447–475.

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

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

Miller, S. and Wherry, L. R. (2019). Four years later: insurance coverage and access to care continue to diverge between aca medicaid expansion and non-expansion states. In *AEA Papers and Proceedings*, volume 109, pages 327–333. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Mullainathan, S. and Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, 31(2):87–106.

Naidu, S. (2012). Suffrage, schooling, and sorting in the post-bellum US South. Technical report, National Bureau of Economic Research.

New, M., Lister, D., Hulme, M., and Makin, I. (2002). A high-resolution data set of surface climate over global land areas. *Climate research*, 21(1):1–25.

Nie, X. and Wager, S. (2021). Quasi-oracle estimation of heterogeneous treatment effects. *Biometrika*, 108(2):299–319.

Nunn, N. (2008). The long-term effects of Africa's slave trades. *The Quarterly Journal of Economics*, 123(1):139–176.

Nunn, N. and Wantchekon, L. (2011). The slave trade and the origins of mistrust in Africa. *American Economic Review*, 101(7):3221–52.

Ogburn, W. F. and Grigg, C. M. (1955). Factors related to the Virgina vote on segregation. *Soc. F.*, 34:301.

Olvera, J. G., Smith, C. W., et al. (2023). The effect of the Affordable Care Act and racial dynamics on federal Medicaid transfers. *Journal of Public Policy*, 43(3):533–555.

Peng, L., Guo, X., and Meyerhoefer, C. D. (2020). The effects of Medicaid expansion on labor market outcomes: evidence from border counties. *Health economics*, 29(3):245–260.

Ransom, R. L. and Sutch, R. (2001). *One kind of freedom: The economic consequences of Emancipation*. Cambridge University Press.

Robinson, P. M. (1988). Root-n-consistent semiparametric regression. *Econometrica: Journal of the Econometric Society*, pages 931–954.

RWJF (2020). 2020 county health rankings key findings. Technical report, University of Wisconsin Population Health Institute and Robert Wood Johnson Foundation.

Sears, D. O., Van Laar, C., Carrillo, M., and Kosterman, R. (1997). Is it really racism?: The origins of white Americans' opposition to race-targeted policies. *The Public Opinion Quarterly*, 61(1):16–53.

Sessions, S. Y. and Lee, P. R. (2008). A road map for universal coverage: Finding a pass through the financial mountains. *Journal of Health Politics, Policy and Law*, 33(2):155–197.

Tesler, M. (2012). The spillover of racialization into health care: How President Obama polarized public opinion by racial attitudes and race. *American Journal of Political Science*, 56(3):690–704.

Voigtländer, N. and Voth, H.-J. (2012). Persecution perpetuated: The medieval origins of anti-semitic violence in Nazi Germany. *The Quarterly Journal of Economics*, 127(3):1339–1392.

Williams, J. (2017). Historical lynchings and contemporary voting behavior of Blacks.

Williamson, V., Skocpol, T., and Coggin, J. (2011). The Tea Party and the remaking of Republican conservatism. *Perspectives on Politics*, pages 25–43.

Winter, N. J. (2008). *Dangerous frames: How ideas about race and gender shape public opinion.* University of Chicago Press.

Yadlowsky, S., Fleming, S., Shah, N., Brunskill, E., and Wager, S. (2021). Evaluating treatment prioritization rules via rank-weighted average treatment effects. *arXiv preprint arXiv:2111.07966*.

8 Figures and Tables

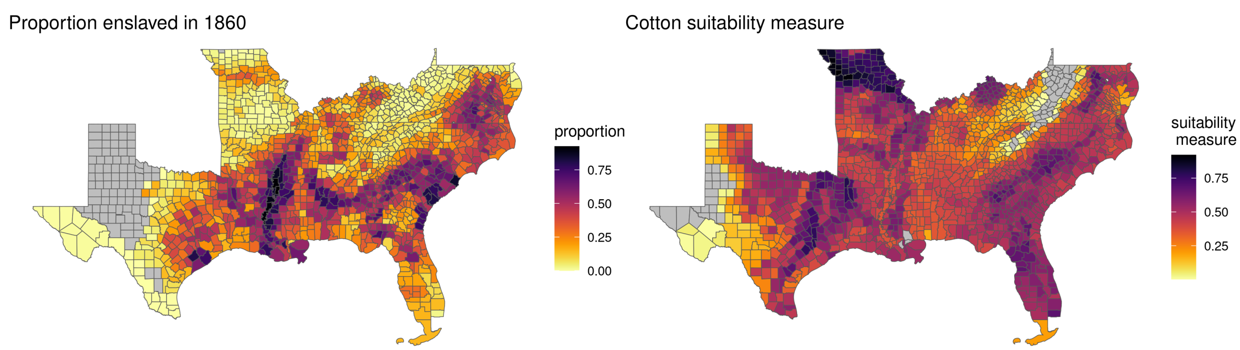


FIGURE 2: The proportion enslaved in 1860 and cotton suitability measure

Note: The map illustrates the across-county variation in the proportion enslaved in 1860 (left) and cotton suitability measure (right). The missing values are represented with grey fills.

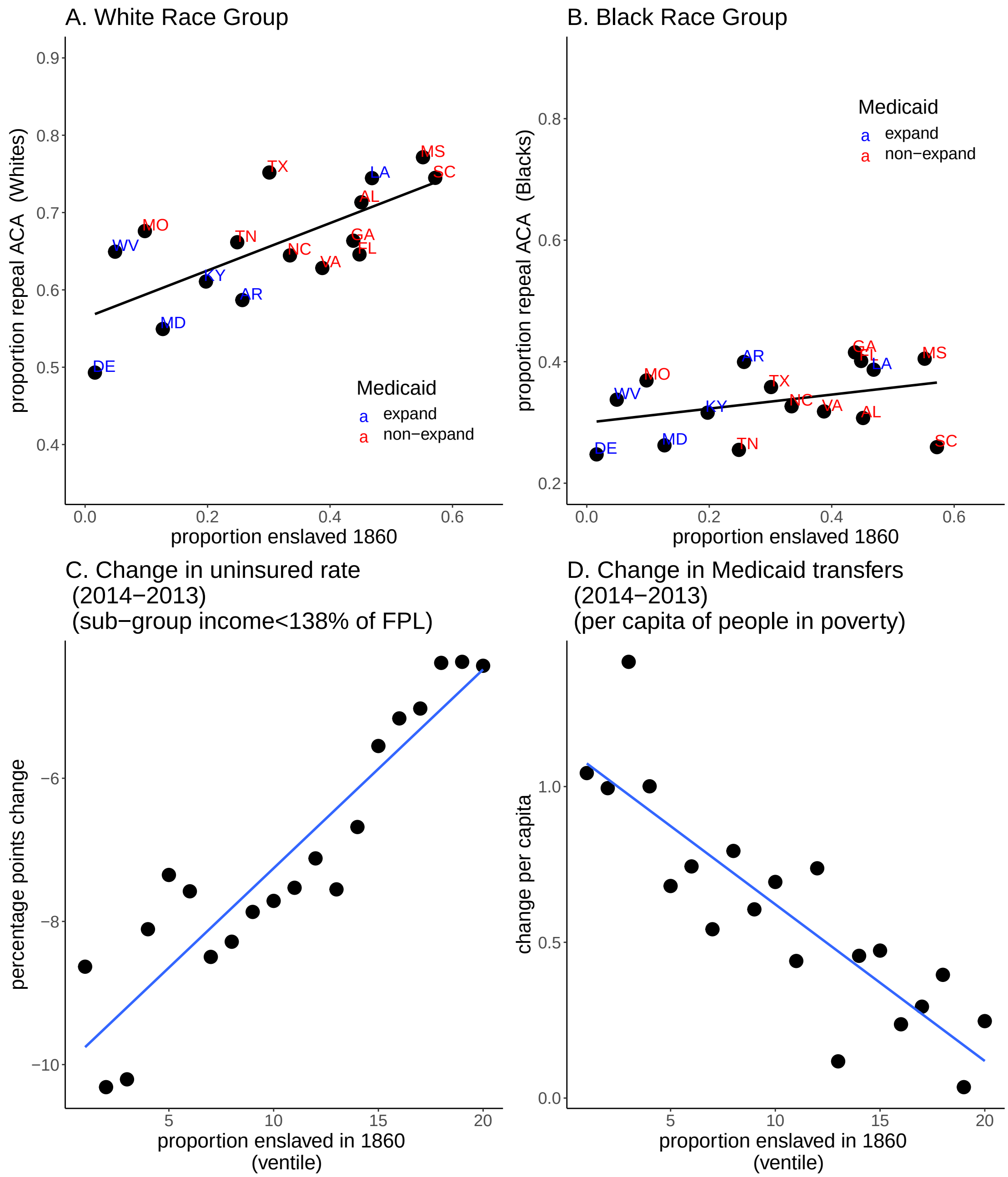


FIGURE 3: Proportion enslaved in 1860, the preference to repeal ACA, and differences in ACA's efficacy

Note: The sub-figures use individual-level CCES data (2014, 2016, 2018) regarding a person's preference to repeal the ACA, aggregated at the state level in Panels A and B. The figures show the correlation between the proportion enslaved in 1860 and the proportion in favor of repealing ACA by racial groups. Panels C and D use changes in uninsured rates between 2013 and 2014 from SAHIE and the change in per capita Medicaid transfers (Bureau of Economic Analysis) between the same years, estimated at the ventile of the proportion enslaved in 1860.

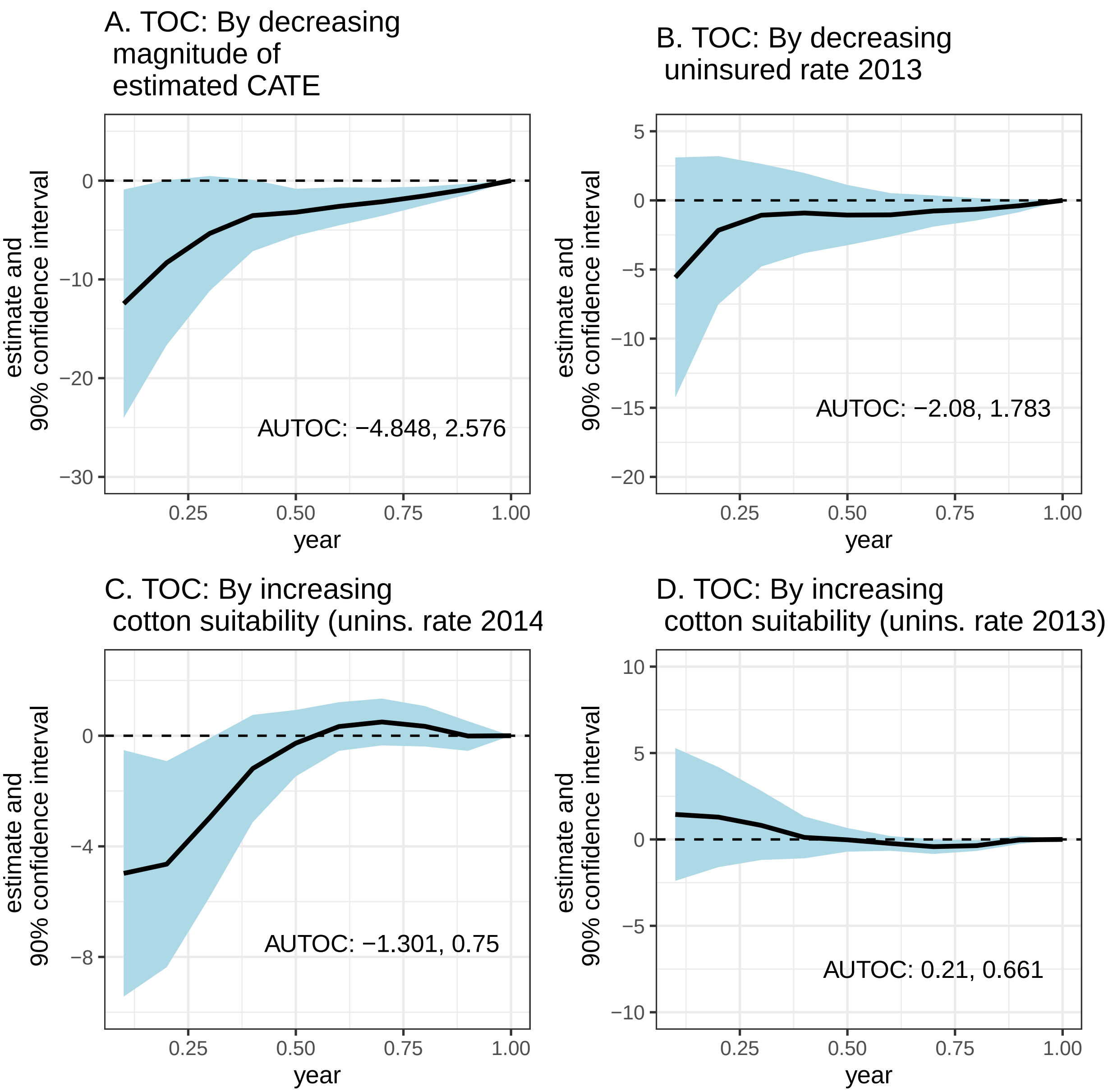


FIGURE 4: Heterogeneity in ATE using rank-weighted average treatment effects (RATE)

Source: Data from SAHIE and other sources discussed in Section 3.

Note: The response variable used for the causal forest is the uninsured rate below 138% of FPL in 2014. The figures plot the targeting operator characteristics curve: $TOC(u;\ S) = E[Y_i(1) - Y_i(0)|F_S(S(X_i)) \geq 1 - u] - E[Y_i(1) - Y_i(0)]$ to document heterogeneity in treatment based on different measures. Here, S is the priority scoring function and the score, $S(.)$, is represented by: i) CATE, ii) uninsured rate below 138% of FPL in 2013, iii) cotton suitability measure (where the response variable used is the uninsured rate when building the forest), and iv) cotton suitability measure (with the uninsured rate in 2013 as the response) in panels A-D. TOC ranks $S(X_i)$ from the lowest to highest value and plots the difference in ATE between the segment of the score above the $(1-u)^{th}$ percentile and the overall ATE, where $0 \leq u \leq 1$. AUTOC provides the summary measure (RATE) of the TOC curve by estimating the area under TOC, along with the standard error. In the absence of significant heterogeneity in treatment both TOC and AUTOC will be no different from 0.

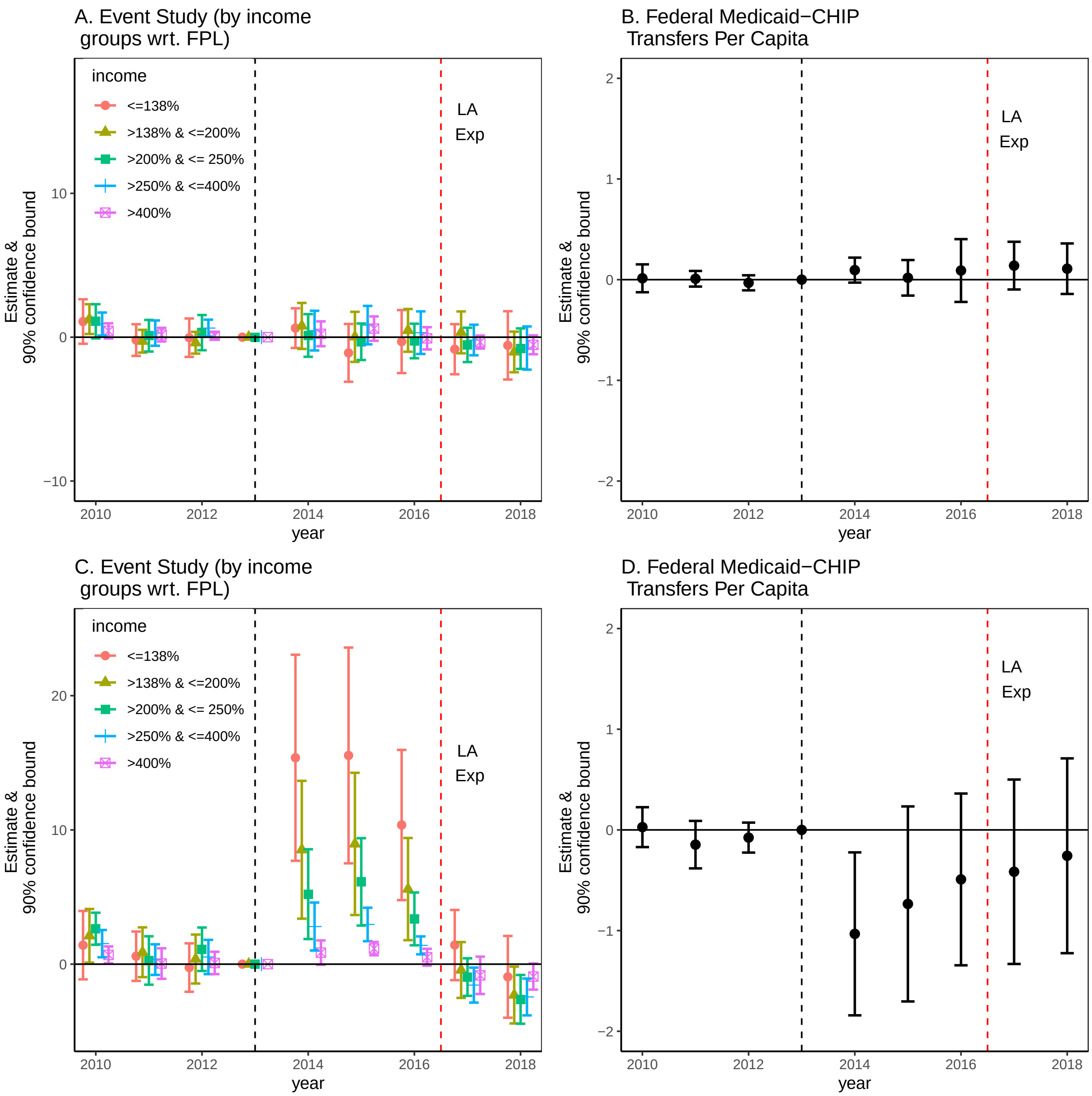


FIGURE 5: The proportion enslaved and the gap in uninsured rates following the reform

Source: SAHIE (Panels A and C) and Bureau of Economic Analysis, data from the Centers for Medicare and Medicaid (Panel B and D).

Note: The figures show estimates of γ_k from equation 4. Panels A-B pertain to non-expansion states, while C-D represents the expansion states. Panel A (C) uses the county level uninsured rates for groups defined by the varying levels of income relative to the FPL. The sample is restricted to individuals between the ages of 18 and 65 in Panels A and C. Panel B (D) uses the federal Medicaid-CHIP transfers per person. The standard errors are clustered at the state level and the error bars represent the 90% confidence intervals. The black dotted lines denote the year prior to the ACA (2013), while the red lines pertain to the time when Louisiana expanded Medicaid through ACA.

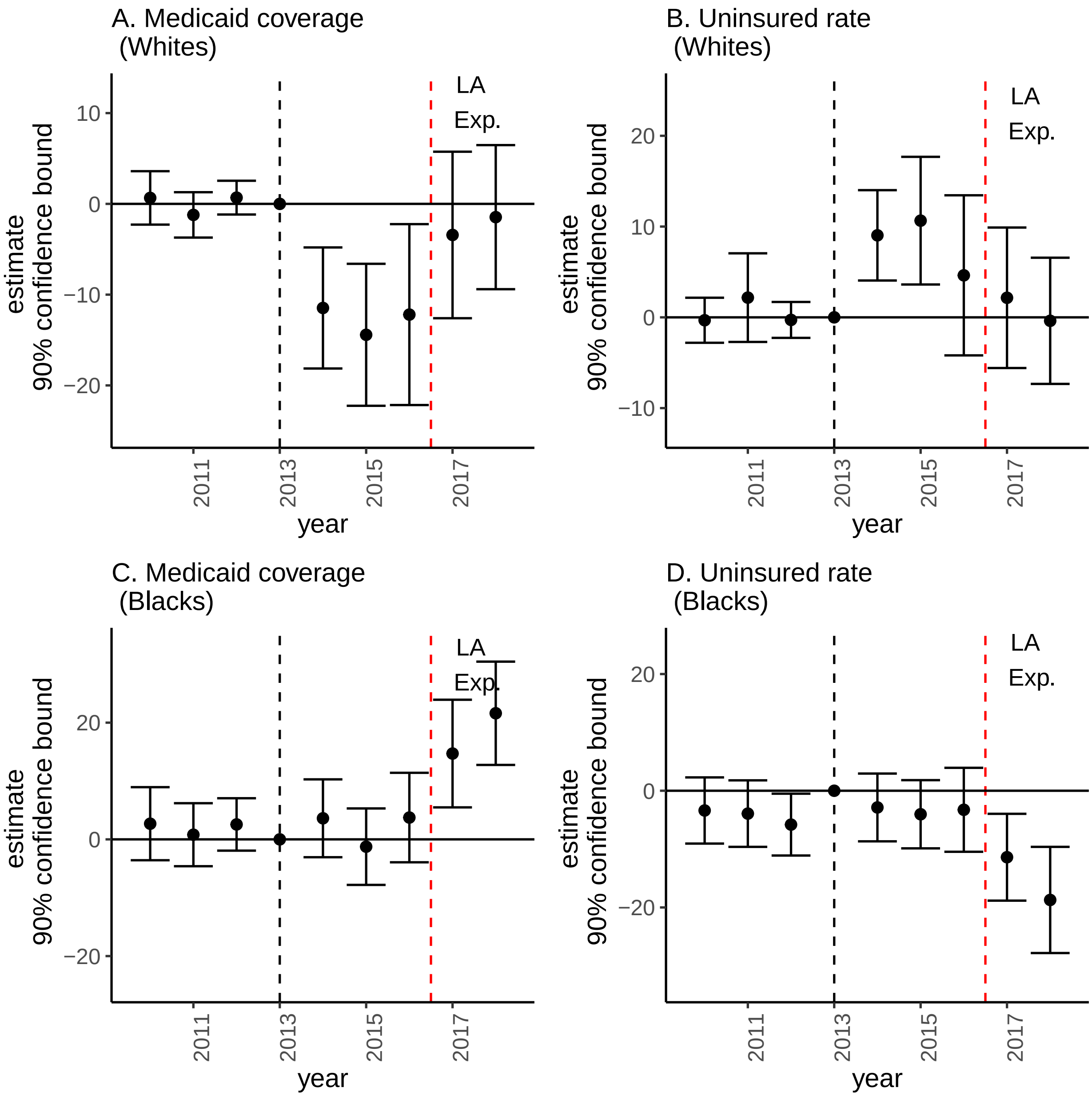


FIGURE 6: The proportion enslaved in 1860 and the gap in uninsured rates by race groups within expansion states

Note: The figures show the estimates from estimating equation 4 for the sample of White and Black Southerners in expansion states using data from ACS aggregated at the PUMA-year-race cell. The ACS sample excludes individuals receiving supplementary security income and non-citizens and pertains to the age group of 18-65 years old with education level less than or equal to high school. Panel A (C) uses the proportion of individuals covered through Medicaid as the dependent variable; Panel B (D) uses uninsured rate. The standard errors are clustered at the state level and the error bars represent the 90% confidence intervals.

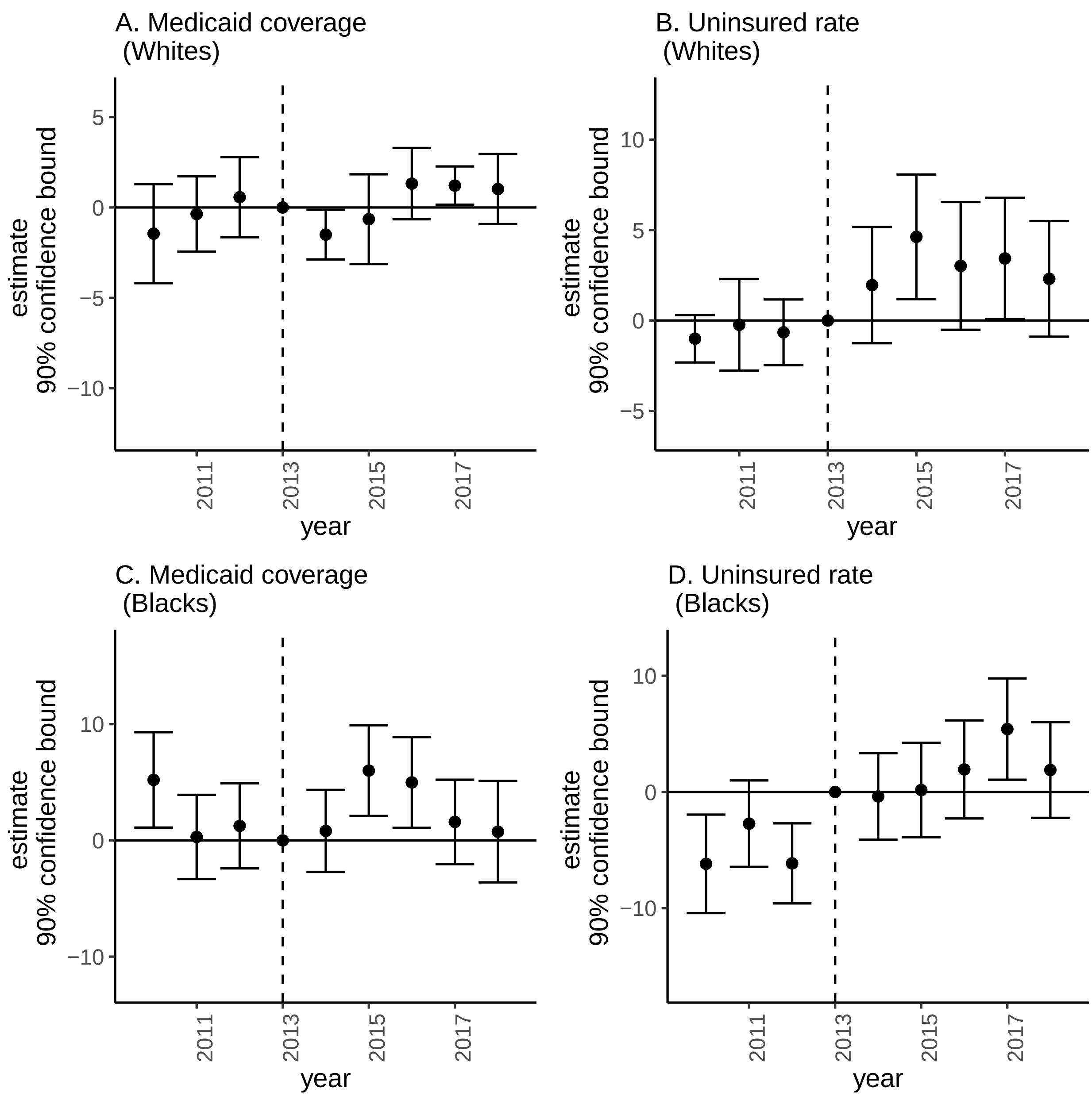


FIGURE 7: The proportion enslaved in 1860 and the gap in uninsured rates by race groups within non-expansion states

Note: The figures show the estimates from estimating equation 4 for the sample of White and Black Southerners in non-expansion states using data from ACS aggregated at the PUMA-year-race cell. The ACS sample excludes individuals receiving supplementary security income and non-citizens and pertains to the age group of 18-65 years old with education level less than or equal to high school. Panel A (C) uses the proportion of individuals covered through Medicaid as the dependent variable; Panel B (D) uses uninsured rate. The standard errors are clustered at the state level and the error bars represent the 90% confidence intervals.

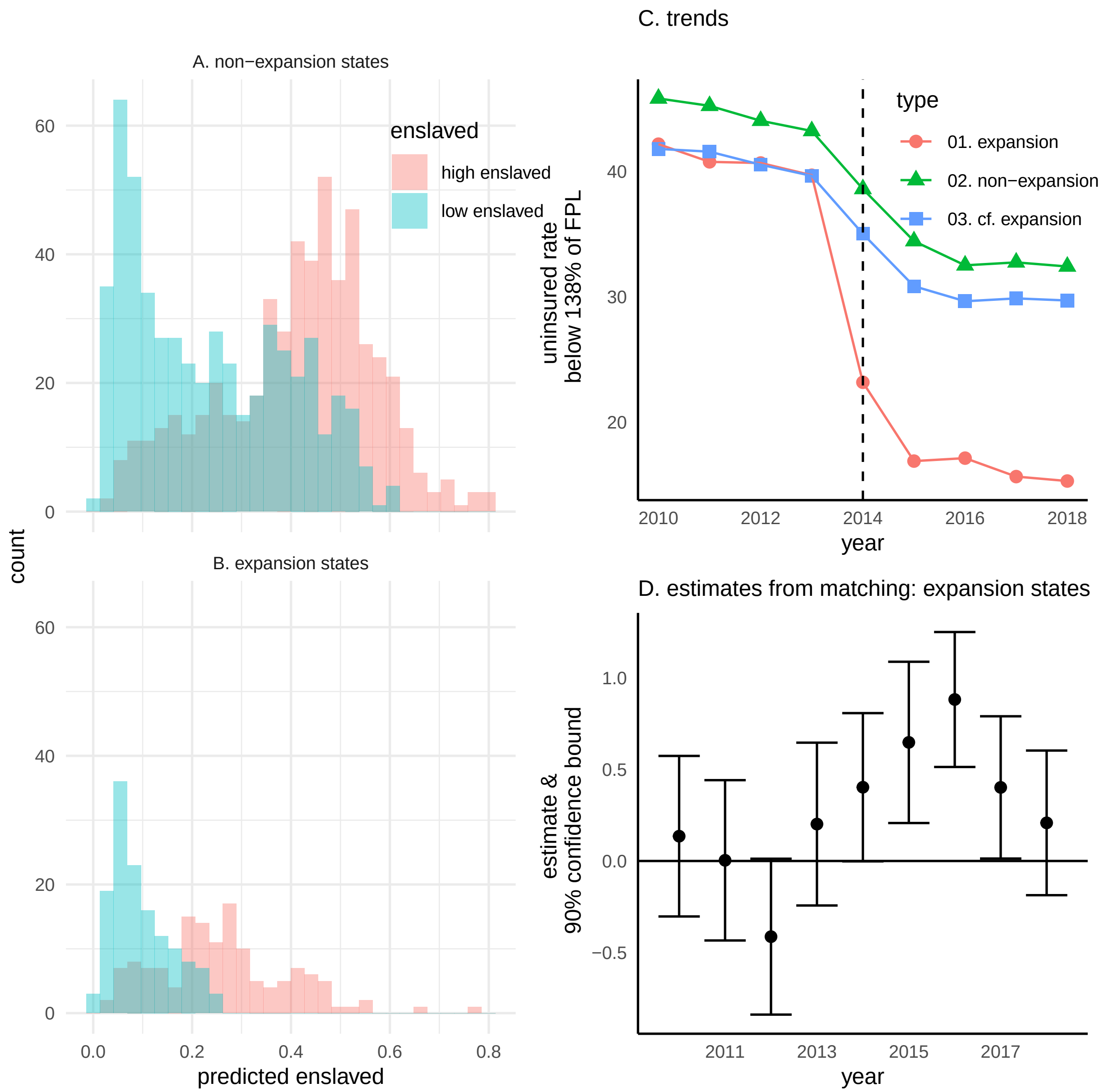


Figure 8: Estimates from the matching approach based on the predicted values of the proportion enslaved in 1860

Note: Panel A (C) shows the distribution of predicted values of the proportion enslaved among counties categorized by high versus low enslaved groups in non-expansion states (expansion states). The high/low enslaved groups are based on the median value of the proportion enslaved within the state. A boosted regression forest model is trained with honest sampling, and the predicted values of the enslaved population are obtained from the out-of-bag observations. The figures in the right column pertain to the matching approach. Panel C depicts trends in uninsured rates across three different groupings: (1) expansion states, (2) non-expansion states, and (3) counterfactual expansion states (hypothetical expansion states in the absence of expansion). In summary, counties with similar predicted values for the proportion enslaved but differing in high versus low enslaved groups are paired with one another. Panel D shows the average difference in uninsured rates across the matched pairs (uninsured rate in high enslaved - low enslaved counties with similar predicted enslaved values). The vertical bars correspond to the 95% confidence intervals obtained from the wild cluster bootstrap.

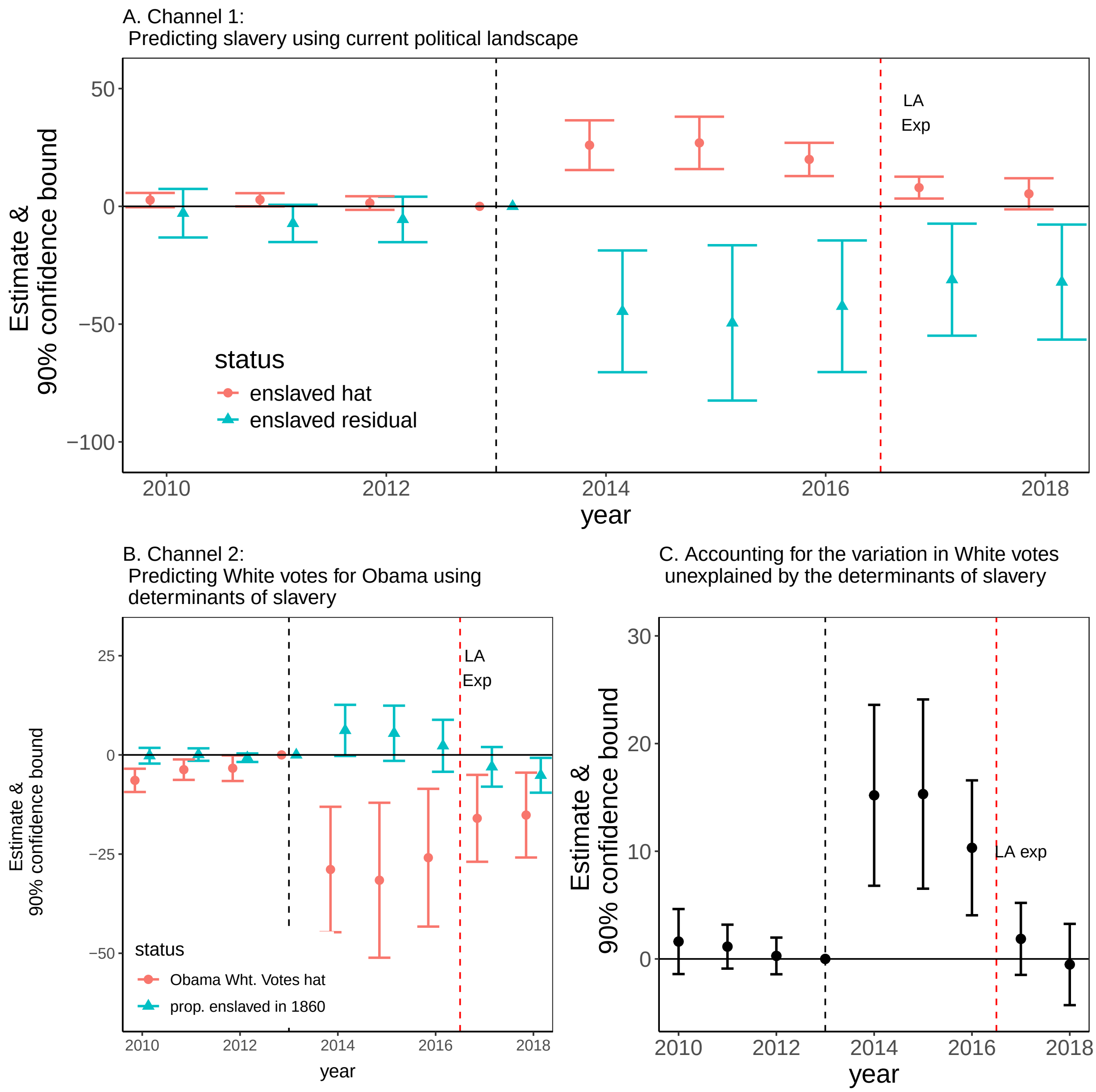


FIGURE 9: The inertia of institutional slavery explains the poor implementation of the ACA through contemporary politics

Note: Panel A uses two separate variations in the proportion enslaved in 1860: one explained by contemporaneous political variables (percent of White votes for Obama, percent of votes for Trump, whether a county is Democrat) and the other unexplained. Panel B uses the determinants of slavery (cotton suitability measure, malaria stability, long-run climate precipitation, and temperature) to predict White votes for Obama in the 2008 election. It shows the relationship between the fraction enslaved in 1860 and predicted White votes for Obama on ACA efficacy. The 90% confidence intervals are represented by the error bars, which are obtained from standard errors clustered at the state level.

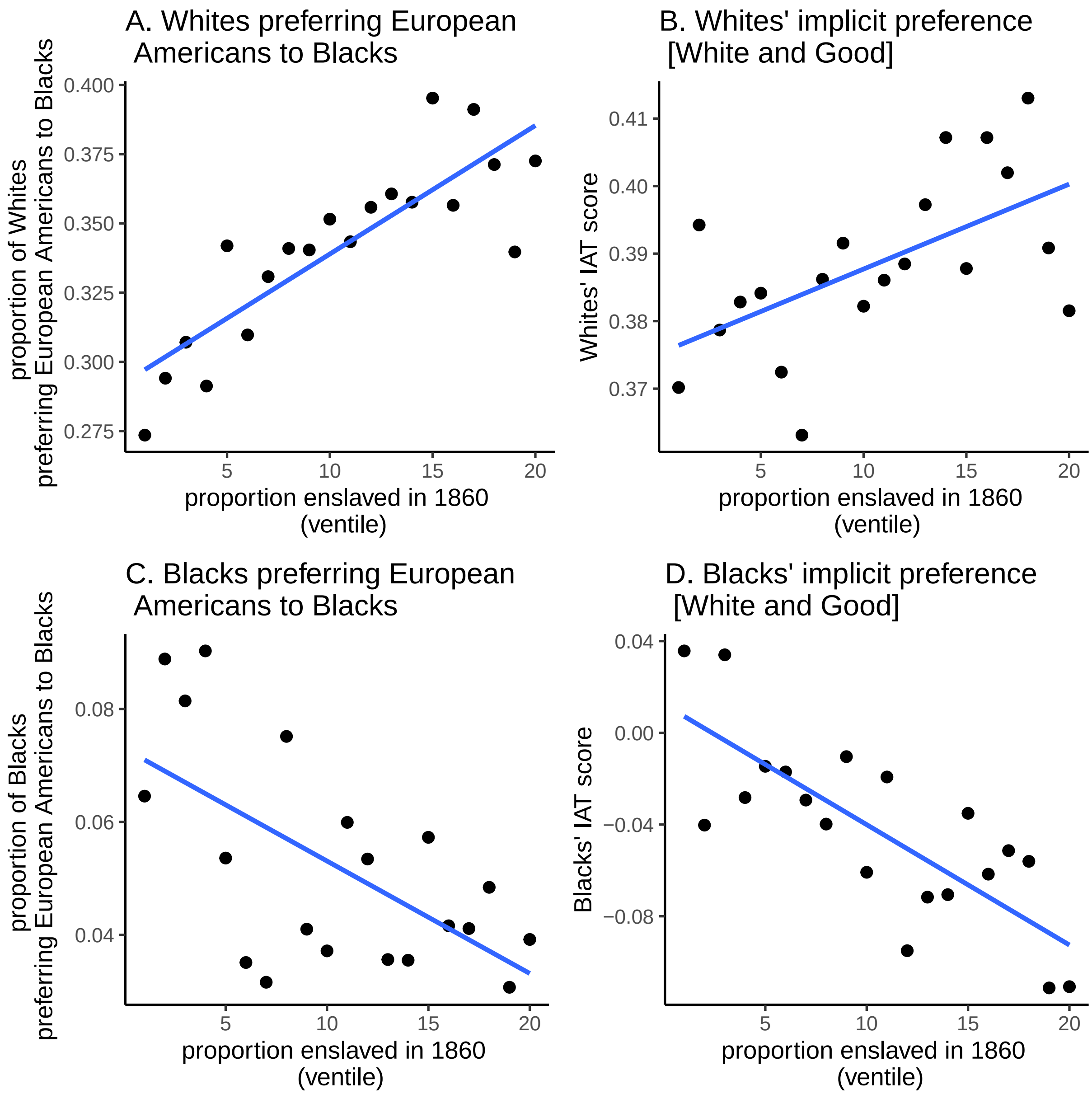


Figure 10: The intensity of slavery measure and racial prejudice

Note: The figure uses data from Project Implicit (years 2010 to 2019) to measure explicit and implicit racial biases. The explicit racial bias is derived from a question that asks whether an individual prefers a certain race in favor of the other. We generate a variable indicating whether a responder prefers European Americans in favor of Blacks. The implicit score pertains to the association between the concepts "Whites" and "good". The data from Project Implicit are aggregated at the county level and merged with historical data.

Table 1: Comparison of ATE using the Causal Forest (CF) and other methods

	naive	DD	ATE.CF	ATE.CF2	ATE.CF3	ATE.CF4
estimate	-15.422	-11.880	-12.517	-11.443	-0.774	-0.086
sd	3.086	2.162	3.011	3.493	1.612	1.356

Note: The response variable used in columns 1 and 3 is the county level uninsured rate below 138% of FPL in 2014. Columns 2 and 4 use the the first difference in uninsured rate between 2014 and 2013. Column 5 uses the county-level uninsured rate below 138% of FPL in 2013, while column 6 uses the first difference in uninsured rate between 2013 and 2012. The estimate in column 1 is based on the naive estimator that evaluates the difference in means between the treated and untreated units. Column 2 reports the difference-in-differences (DD) estimate obtained from first differencing. The other columns summarize the conditional average treatment effect (CATE) estimates obtained by using causal forest as discussed in Section 4.1.

Table 2: The negative relationship between slavery and ACA implementation is suppressed in areas that mechanized earlier

	Unins. rate (138% FPL)	Unins. rate	Medicaid transfer pc	Unins. rate (138% FPL)	Unins. rate	Medicaid transfer pc
	Expansion states			Non-expansion states		
	(1)	(2)	(3)	(4)	(5)	(6)
Post ACA × prop.enslaved 1860	13.79	7.544	-0.8039	-1.064	-0.2852	0.1267
	(5.100)	(1.983)	(0.7495)	(1.392)	(0.5617)	(0.0776)
Post ACA × High Tractor	-0.9035	1.626	-0.3139	0.2022	0.4649	0.0188
	(1.551)	(0.6920)	(0.2176)	(0.3627)	(0.2898)	(0.0368)
Post ACA × prop.enslaved 1860 × High Tractor	-2.658	-5.068	0.7797	0.0568	-0.4136	0.0178
	(3.211)	(1.418)	(0.5622)	(0.9986)	(0.5849)	(0.0809)
Observations	3,069	3,069	3,069	8,883	8,883	8,676
R^2	0.95789	0.95763	0.94318	0.96012	0.96899	0.95667
Year FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓

Columns 1-3 and 4-6 pertain to expansion and non-expansion states, respectively. Columns 1 (4) use uninsured rate below 138% of FPL, columns 2 (5) use the overall uninsured rate (overall population), and colums 3 (6) use Medicaid transfers per capita. The level of mechanization is represented by the change in tractors between 1940 and 1930; "High Tractor" indicates whether a county experienced change in mechanization that is above the median. The post policy variable represented by "policy" indicates year 2014 and beyond. All specifications include the interaction between uninsured rate (below 138% of FPL) in 2013 and post policy indicator, county and year fixed effects.

A Data Source of the County Level Variables Used

A.1 Historical Variables

- Proportion enslaved (1860): The proportion of the enslaved population is obtained from the 1860 U.S. Census. The variable is extracted from Acharya et al. (2016) replication files.

- Proportion of Blacks in 1860: The variable is obtained from the 1860 Census and extracted from Acharya et al. (2016) replication files.

- Black sharecroppers (1930): The fraction of Blacks involved in sharecropping in 1930 is obtained from Althoff and Reichardt (2022).

- Cotton suitability measure: This variable measures the soil suitability for cotton farming. It is obtained from the Acharya et al. (2016) replication files. The authors construct the cotton suitability measure using data from the UN Food and Agriculture Organization (FAO). Readers are directed to the Acharya et al. (2016) study for more details.

- Malaria stability index: This variable represents the malaria transmission intensity and is a predicted measure of incidence. The county-level index is constructed using the raster file provided by the Kiszewski et al. (2004) study. The stability index is constructed at a 0.5×0.5 degree resolution, and it predicts the risk of malaria as the function of both the characteristics of mosquitoes prevalent in the area and climate variables (long-run temperature and precipitation). The raw raster file can be downloaded following the link: `https://sdgpolicyinitiative.org/gmresearch/`. Similar index is used in Esposito (2022). The county-level variation in malaria stability index is shown in Panel A, Figure A1.

- Total population in 1860: The total population in 1860 is extracted from the 1860 US Census.

- Proportion of small farms in 1860: This represents the proportion of farms smaller than 50 acres in a county in 1860 and is extracted from Acharya et al. (2016) replication files.

- County area in 1860: This represents the county area in 1860 and is extracted from the Acharya et al. (2016) study.

- Average farm value per acre of an improved land in 1860: This represents the total improved acreage in 1860 and is obtained from the Acharya et al. (2016) replication files.

- Access to railroad and waterways in 1860: These variables measure the access to mobility in 1860 based on county boundaries in 2000. The variables are extracted from Atack (2016) and Atack (2015).

- Lynching rate: This variable measures the total number of lynchings that took place between 1882–1930 divided by the county level population in 1920. The lynching numbers are based on Project Hal `https://people.uncw.edu/hinese/hal/hal%20web%20page.htm`.

- Value of tobacco, cotton, rice, and sugar as the percent of the total agriculture output in 1860: These variables are obtained from Althoff and Reichardt (2022).
- Percentage of Democrat votes in presidential elections between 1880 to 1964: The historical political outcomes are obtained from Clubb et al. (2006).
- Number of Rosenwald schools: This variable counts the number of Rosenwald schools used in the Aaronson and Mazumder (2011) study.
- Total Hill-Burton expenses between 1947 and 1971: Data regarding Hill-Burton expenses is obtained from Heidi L. Williams.
- County-level health departments: Data for county-level health departments are obtained from Hoehn-Velasco (2018).
- Precipitation and average temperature: The county-level long-term climate variables are constructed by using 10' latitude/longitude data set of mean monthly surface climate for the period 1961-1990. The climate variables are obtained from the Climate Research Unit `https://crudata.uea.ac.uk/cru/data/hrg/tmc/`. Readers are directed to New et al. (2002) for more details. The averages of long-term precipitation and temperature are plotted in Figure A1.
- Elevation: The elevation data file is constructed using the raw data obtained from the Climate Research Unit.
- Land ruggedness: The land ruggedness variable is obtained from Hornbeck and Naidu (2014) replication files.

A.2 Contemporary Variables

1. Proportion of Blacks and Whites in 2010: These variables are constructed by dividing the count of Blacks (Whites) by the total population in 2010. The population variables are obtained from the Survey of Epidemiology and End Results (SEER). The data is extracted from the NBER website `https://www.nber.org/research/data/survey-epidemiology-and-end-results-seer-us-state-and-county-population-data-age-race-sex-hispanic`.
2. Total population in 2010: The data is extacted from SEER.
3. Estimated White vote share for President Obama: This variable estimates the proportion of White votes for Obama during the 2008 presidential election using data from the Cooperative Congressional Election Study (CCES) respondents. This is the same variable used in Acharya et al. (2016) as one of the outcomes. It is obtained from the Acharya et al. (2016) replication files.
4. Vote share for Trump: The county-level vote share for Trump comes from ICPSR.

5. Whites' household income at age 35: This variable is extacted from the Opportunity Atlas https://www.opportunityatlas.org/.

6. Per capita income and poverty rate in 2010: These variables are extracted from the Small Area Income and Poverty Estimates (SAIPE) Program https://www.census.gov/programs-surveys/saipe/data.html.

7. PM 2.5 measure in 2010: The county-level PM 2.5 measures are constructed using the replication codes and raw data provided in Currie et al. (2023) replication files. Currie et al. (2023) obtain the PM 2.5 measure data from Di et al. (2016a,b).

8. Percent with college (high school) degree in 2010: The education variables come from the National Center for Education Statistics.

9. Unemployment rate in 2010: The county-level unemployment is obtained from the Bureau of Labor Statistics (BLS).

10. Rural-Urban classification: The 2013 Urban-Rural classification is based on the variable developed by the National Center for Health Statistics (NCHS). All counties in the United States are assigned to one of the six categories: *a*) large central metro, *b*) large fringe metro, *c*) medium metro, *d*) small metro, *e*) micropolitan, and *f*) noncore.

B Additional Results

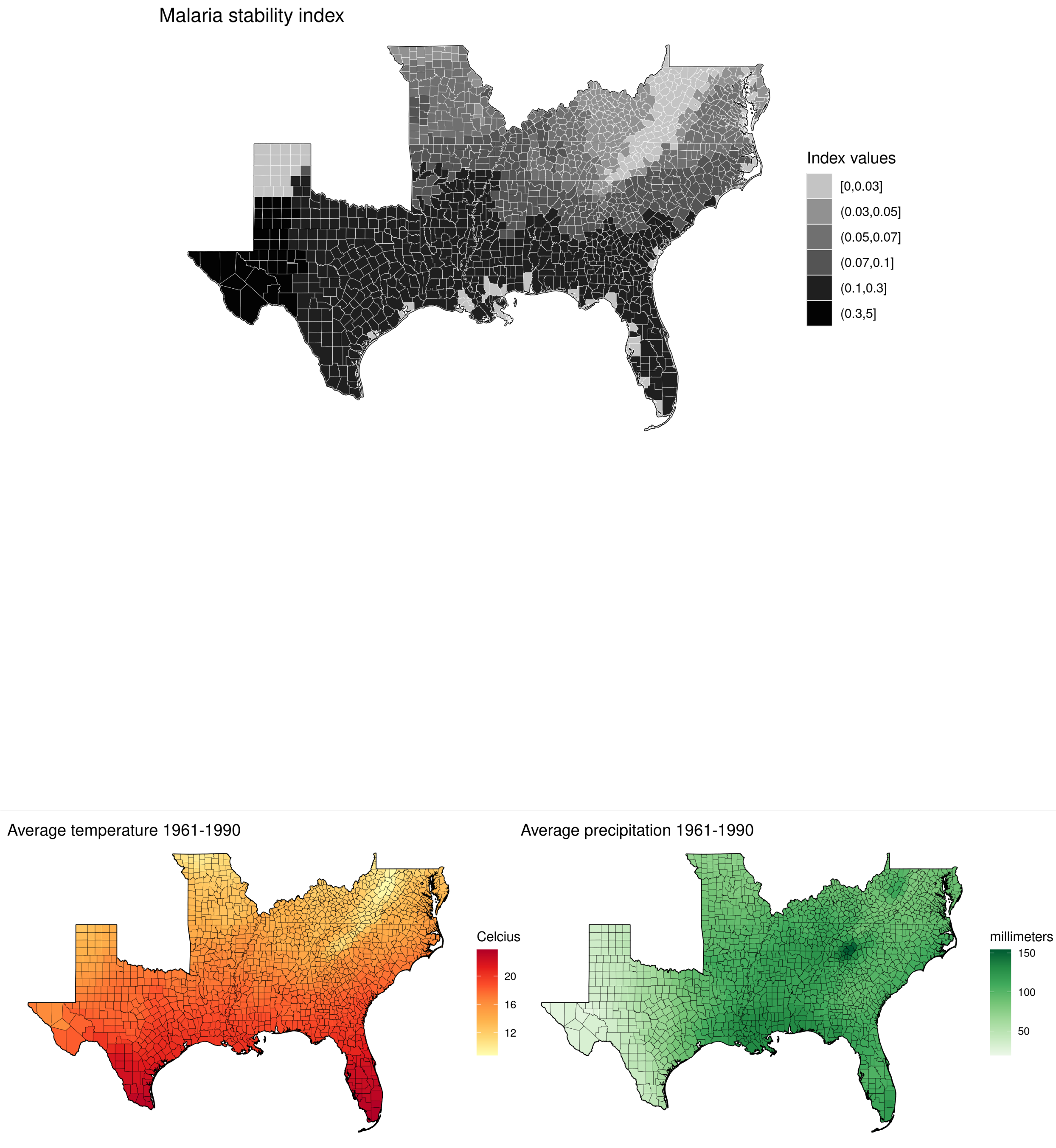
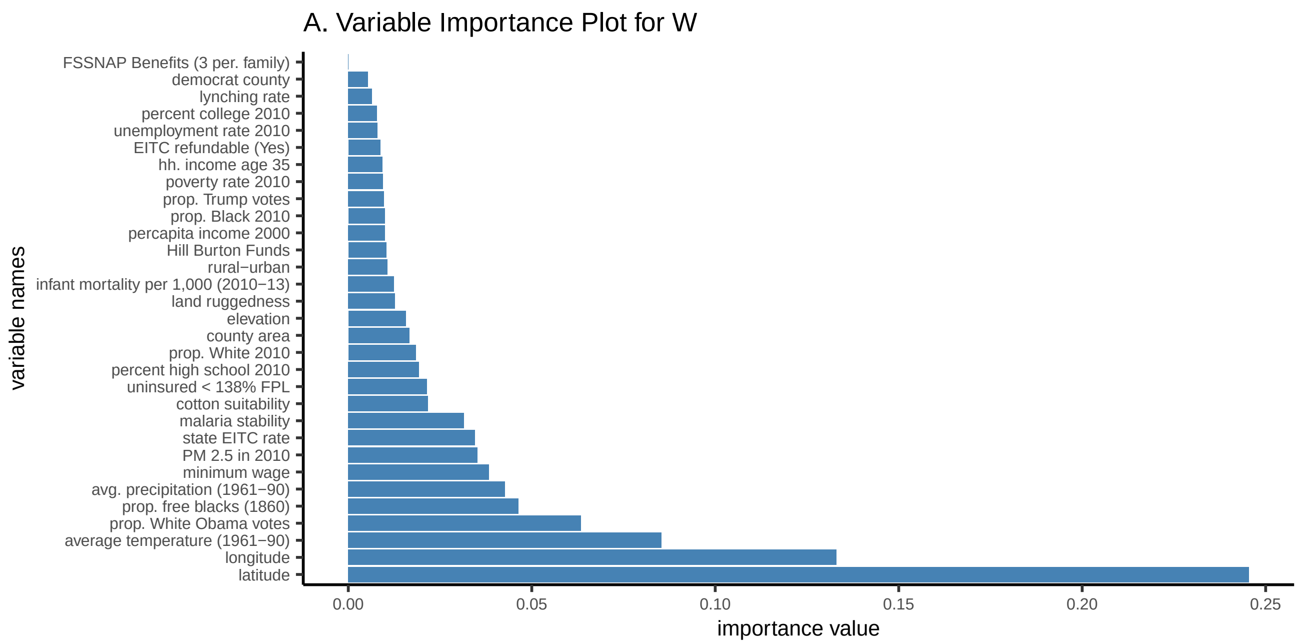


Figure A1: Malaria stability, long-term temperature and precipitation



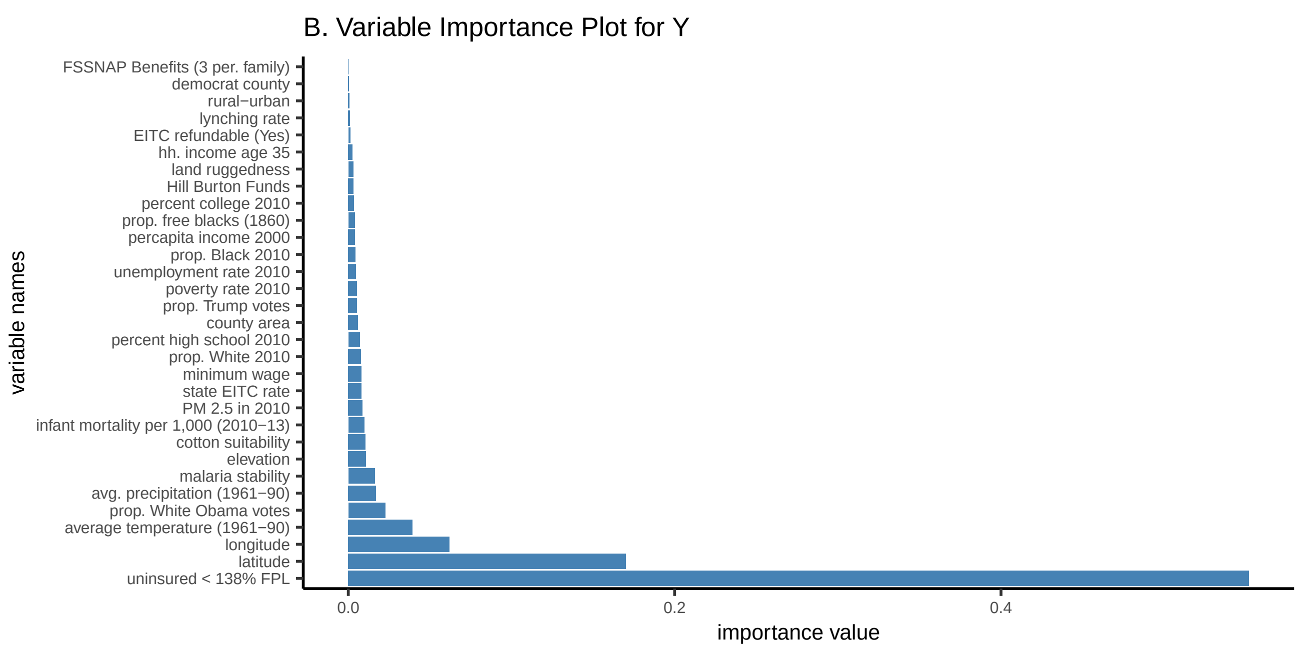


Figure B2: VIP Plot

Note: The figures show variables that are important in forming regression forests for the treatment, W, and uninsured rate in 2014, Y.

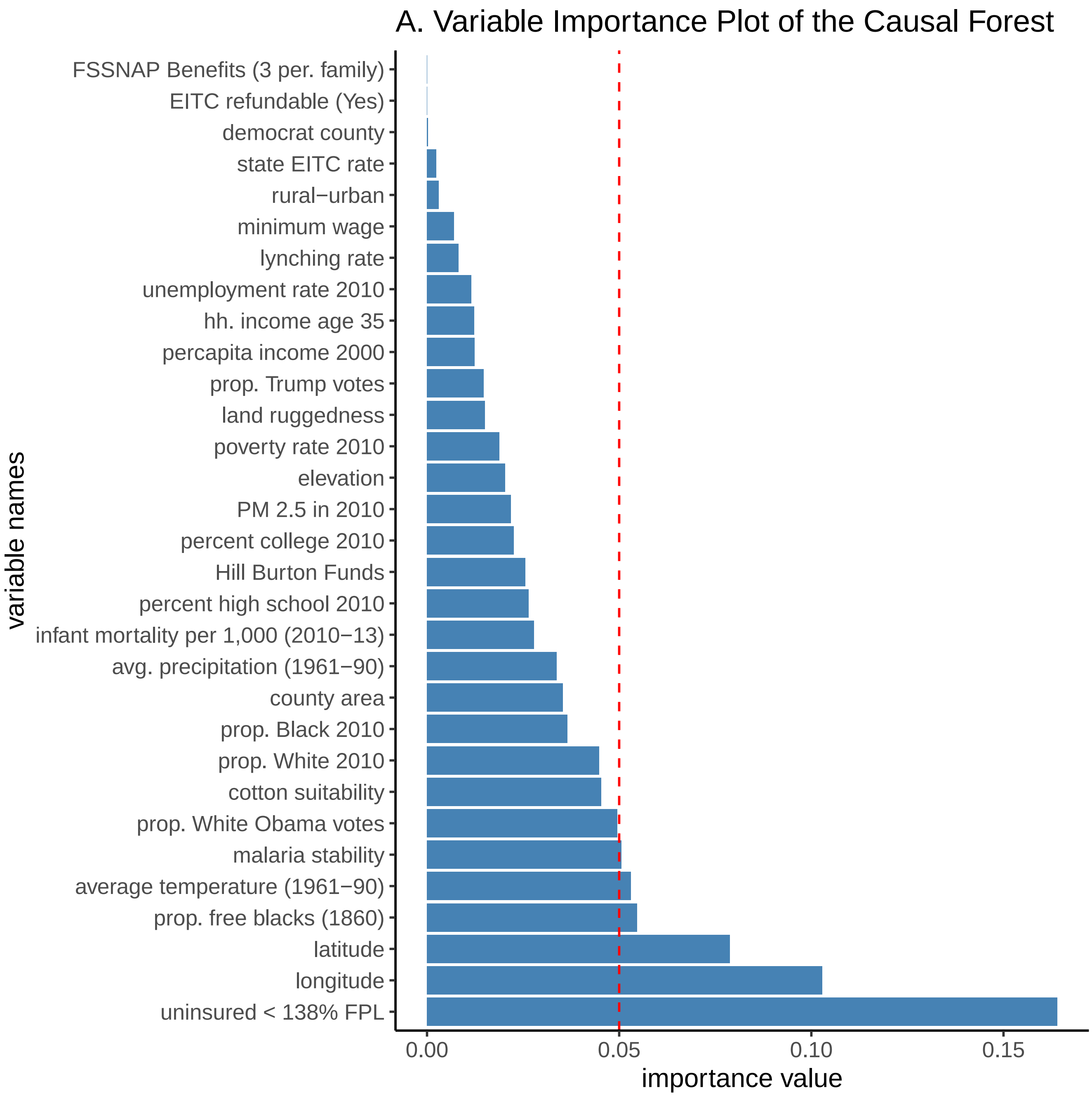
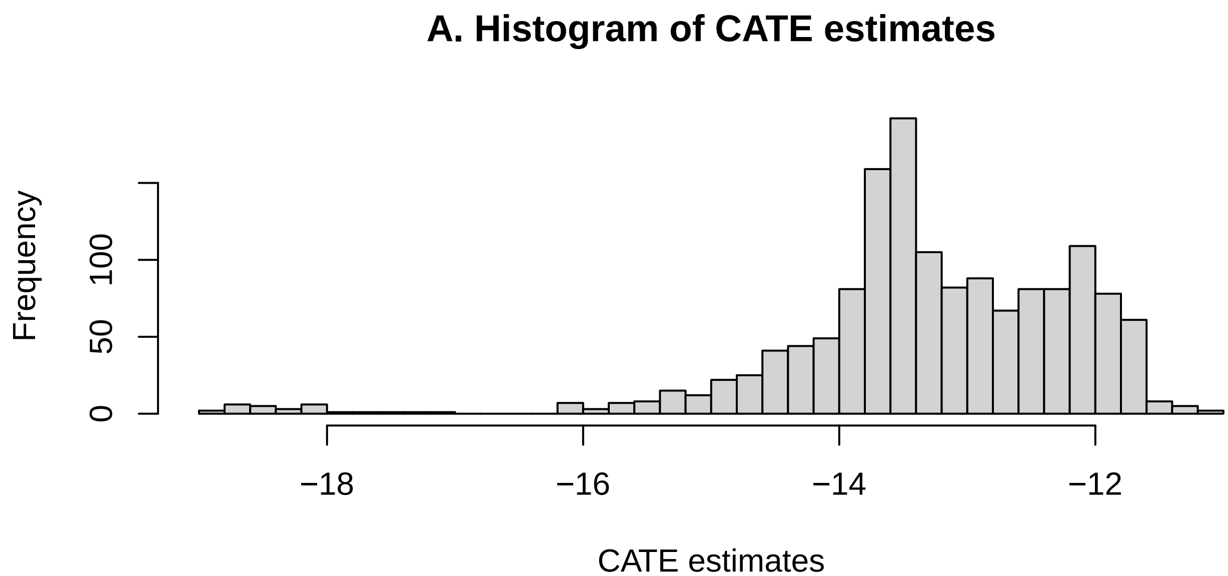


Figure B3: VIP Plot from Causal Forest

Note: The figure shows the level of importance of the variables in forming splits while building the Causal Forest model.



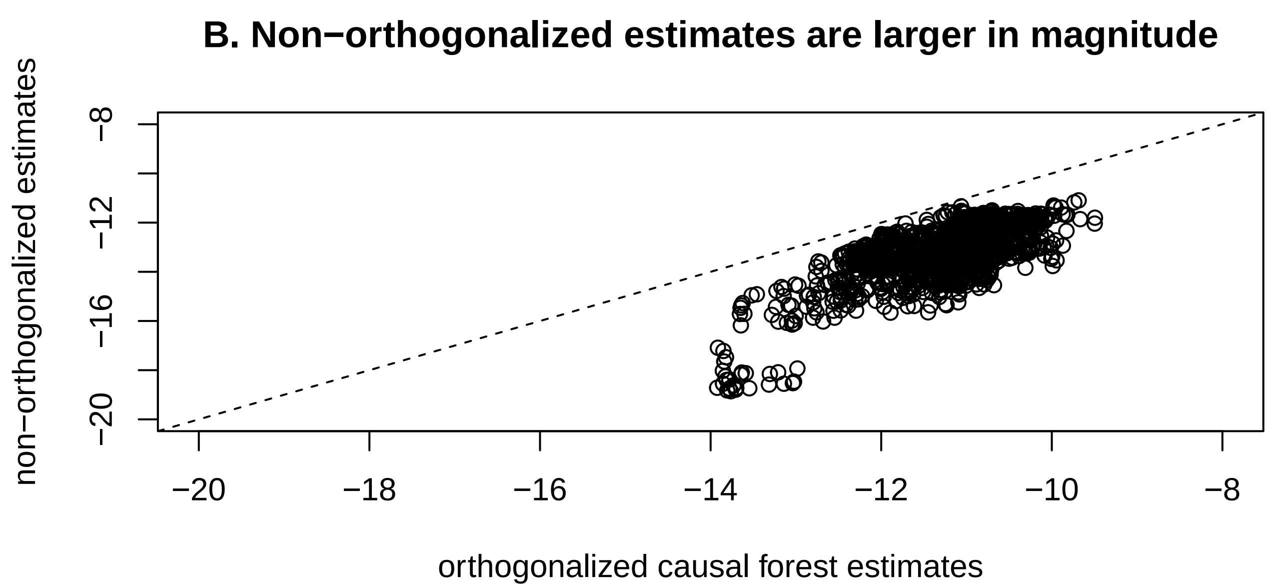


Figure B4: Panel A. CATE estiamtes; Panel B. Comparison between orthogonalized versus non-orthogonalized forests

Note: The sub-figure in Panel A shows the histogram of CATE estimates obtained from CF after orthogonalization as discussed in Section 4.1. The sub-figure in Panel B shows the relationship between CATE estimates from CF following orthogonalization versus CF run on trivially centered outcomes using the means of W and Y.

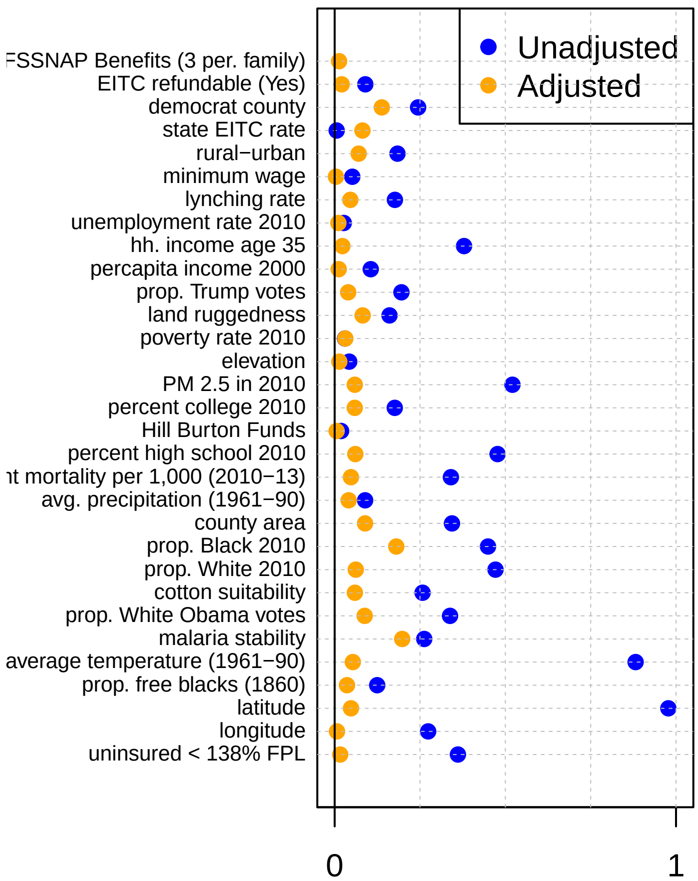


Figure B5: Adjusted and unadjusted difference in means among the covariates

Note: The figure shows the absolute value of the standardized difference in means between the treatment (expansion) and control (non-expansion) units. The unadjusted difference represents the simple difference in means between the treated and control units. The adjusted mean difference plots the absolute difference in means once covariates are adjusted using inverse propensity weights.

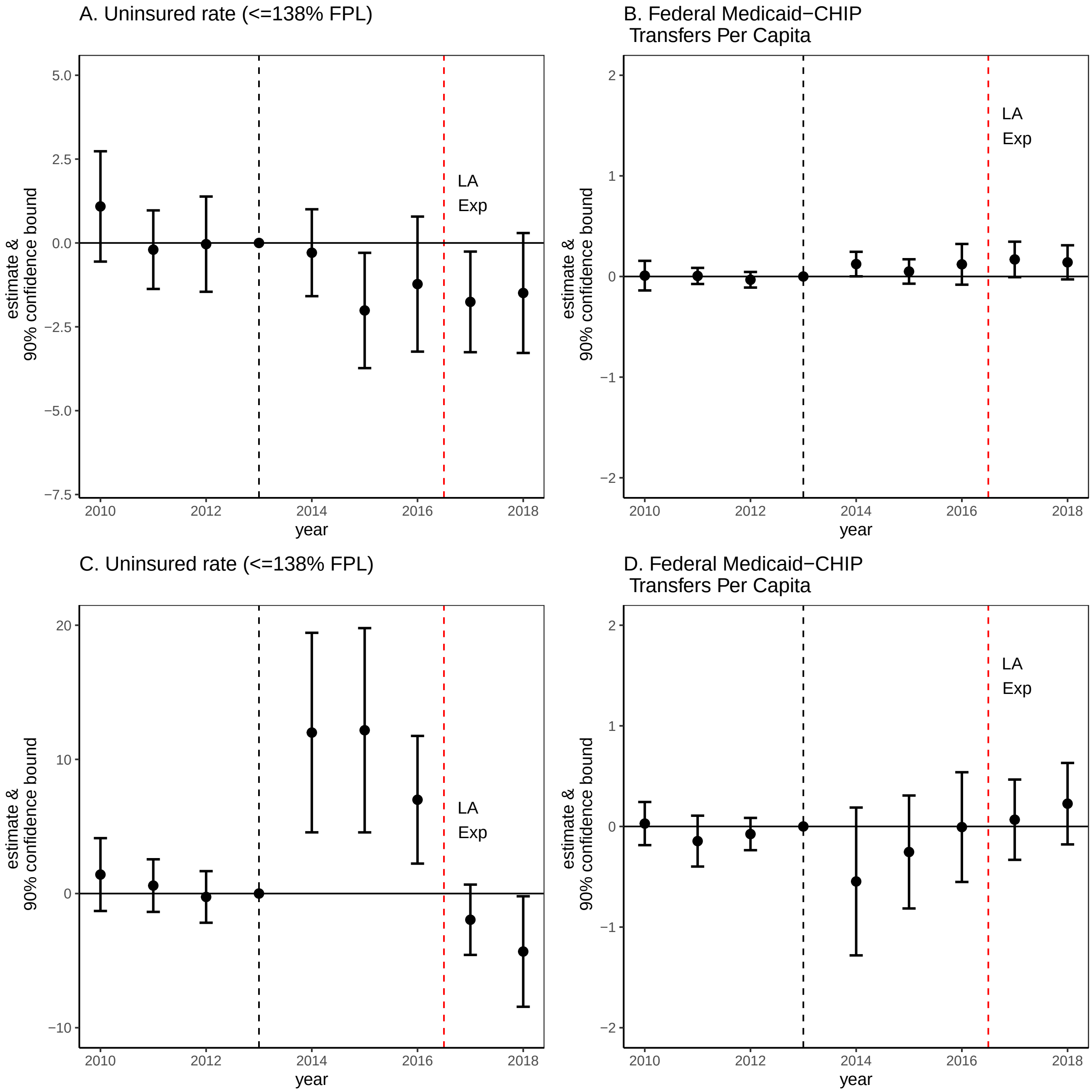


FIGURE B6: SAHIE event study estimates after accounting for the selected covariates from double step Post LASSO

Note: Panels A, B and C, D pertain to non-expansion and expansion states, respectively. The figures show the event study estimates after controlling for the selected variables using double step post LASSO approach following Belloni et al. (2014). The selected variables are interacted with the post-policy indicator before entering the specification. The black vertical dashed lines denote the year prior to the ACA (2013), while the red line marks the timing of Louisiana's Medicaid expansion. The error bars present the 90% confidence intervals that are obtained using standard errors clustered at the state level.

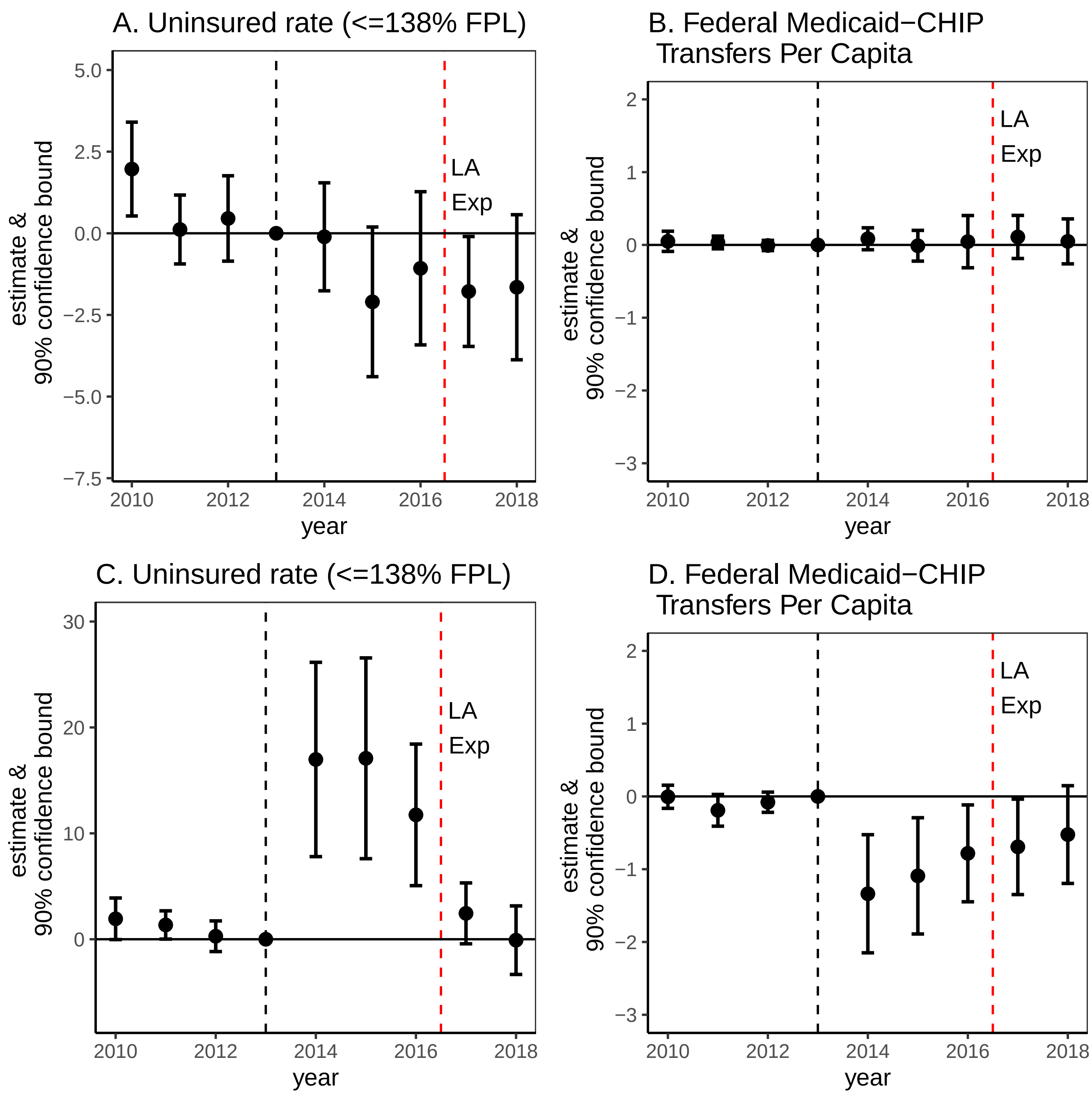


FIGURE B7: SAHIE event study estimates after instrumenting the proportion enslaved in 1860

Note: The figures show estimates using the predicted values of the proportion enslaved in 1860 obtained using a random forest model and instrumented by the cotton suitability measure, malaria stability index, and long-run climate variables. The random forest predictions are based on out-of-bag observations. The estimates are obtained from running the specification similar to equation 4 but using the predicted slavery measure. The vertical black dashed lines denote the year prior to ACA (2013), while the red line marks the timing of Louisiana's Medicaid expansion. The error bars present the 90% confidence intervals that are obtained using standard errors clustered at the state level.

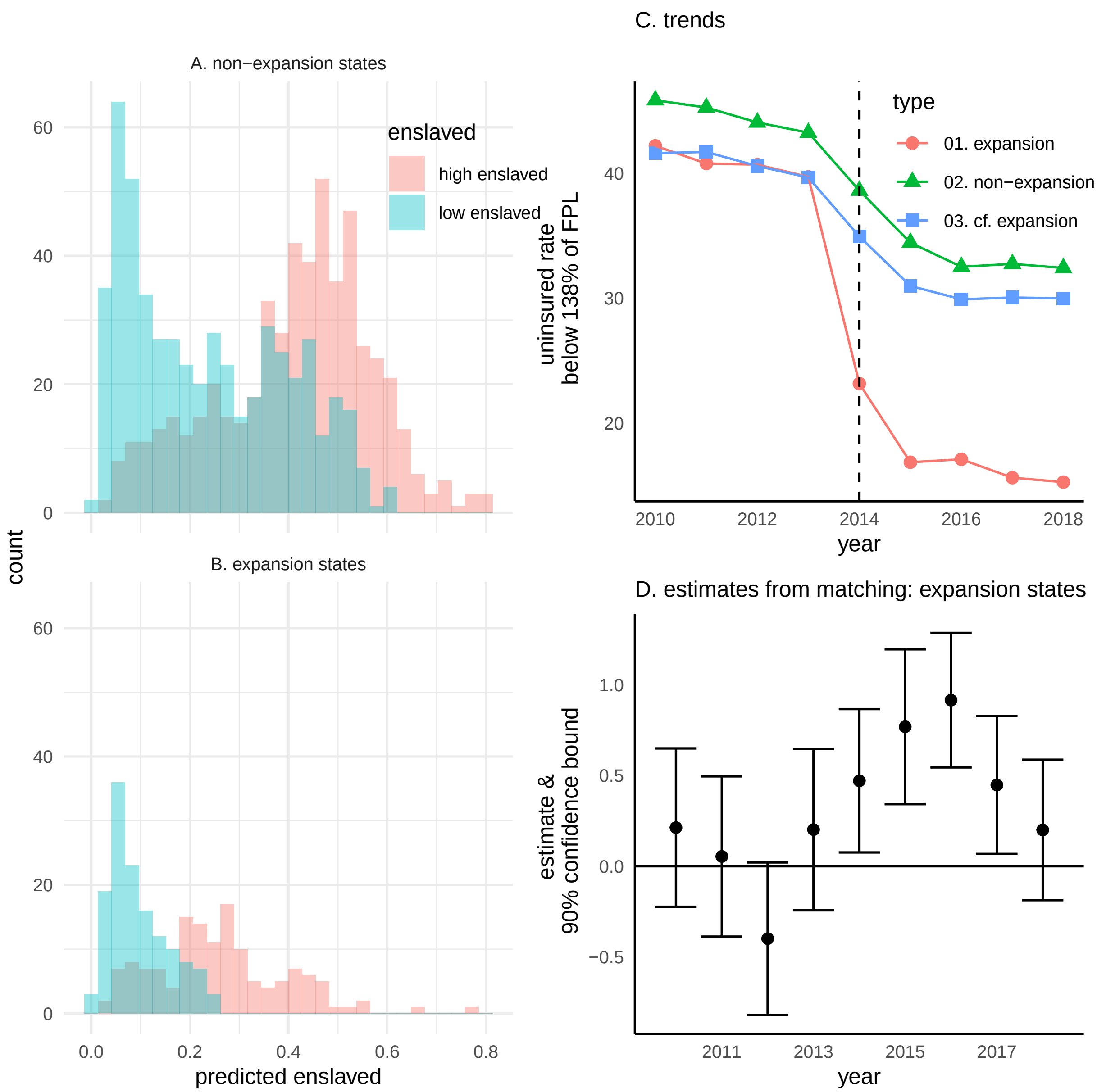


FIGURE B8: Estimates from matching based on the predicted values of the proportion enslaved

Note: The histogram in Panel A pertains to the non-expansion Southern states bordering the expansion states, while the one in Panel B represents expansion states. The histograms show the distribution of predicted values of the proportion enslaved among counties across high versus low enslaved groups. The high/low enslaved groups are based on the median value of the proportion enslaved within the state. Panel C shows trends in uninsured rates across expansion, non-expansion, and counterfactual expansion states (hypothetical expansion states in the absence of expansion).

A boosted regression forest model is trained with honest sampling and the predicted values of enslaved population are obtained from the out-of-bag training samples. In summary, counties with similar predicted values on the proportion enslaved but across high vs. low enslaved groups are paired with one another. The average difference between uninsured rate across the matched pairs (uninsured rate in high enslaved - low enslaved counties with similar predicted enslaved values) after adjusting for the potential confounders are plotted in Panel D. The vertical bars correspond to the 95% confidence intervals obtained from the wild cluster bootstrap.

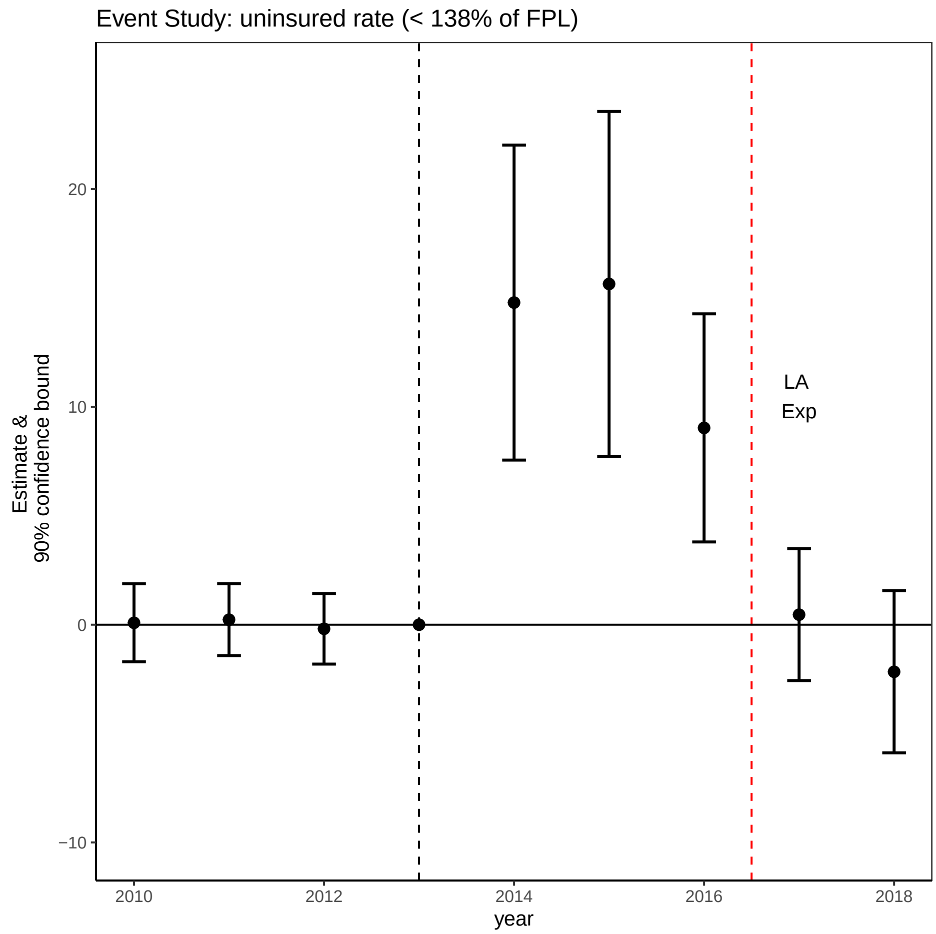


Figure B9: SAHIE event study estimates using the counterfactual for the expansion states

Note: The figure shows event-study estimates using the counterfactual of expansion states as the comparison group for the expansion states. The counterfactual is created using all the non-expansion Southern states. The analysis is conducted at the county level. The estimates are obtained from running a specification similar to equation 4 but comparing outcomes among counties in expansion states to their counterfactuals. The vertical black dashed line denotes the year prior to the ACA (2013), while the red line marks the timing of Louisiana's Medicaid expansion. The error bars represent the 90% confidence intervals that are obtained using standard errors clustered at the state level.

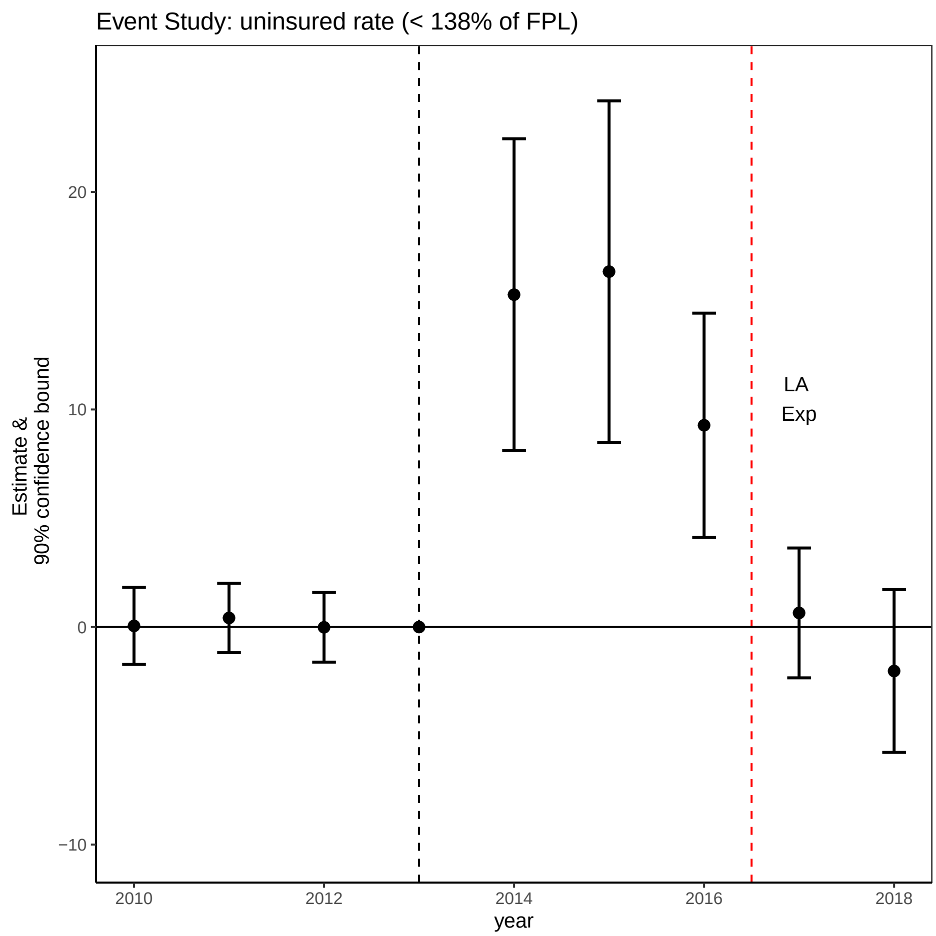


Figure B10: SAHIE event study estimates using the counterfactual for the expansion states

Note: The figure shows event-study estimates using the counterfactual of counties in the expansion states as the comparison group. The counterfactual is created using only the non-expansion Southern states bordering the expansion states. The analysis is conducted at the county level. The estimates are obtained from running a specification similar to equation 4 but comparing outcomes among counties in expansion states to their counterfactuals. The vertical black dashed line denotes the year prior to the ACA (2013), while the red line marks the timing of Louisiana's Medicaid expansion. The error bars represents the 90% confidence intervals that are obtained using standard errors clustered at the state level.

Table B1: Descriptive statistics at the county level

Table B2

Statistic	N	Mean	St. Dev.	Min	Max
pslave1860	1,341	0.287	0.219	0.000	0.924
sahieunins138_yr13	1,459	42.567	7.663	20.000	68.200
mort_total_000_yr10.13	1,451	9.611	1.320	4.574	14.916
prop_black_2010	1,457	0.170	0.182	0.002	0.858
prop_white_2010	1,457	0.812	0.183	0.140	0.996
percap_income10dol_2000	1,408	28,121.430	6,384.704	12,986.420	66,517.720
unp_2010	1,459	10.257	2.737	3.900	26.300
StateMinimumWage	1,459	7.022	0.712	5.150	7.930
rural_urban_code2013a	1,459	4.722	2.662	1	9
p_highschool2010	1,459	35.468	6.664	9.100	70.700
p_college2010	1,459	17.360	8.501	3.700	72.800
povertyrate_allage_2010	1,459	19.528	6.402	3.100	43.300
hhinc35_w	1,454	45,181.680	6,412.709	26,656	72,951
pTrump	1,458	0.653	0.160	0.084	0.946
democrat_county	1,459	0.175	0.380	0	1
wht.obama.vote	1,314	0.274	0.134	0.000	0.847
pm2.5_2010	1,459	10.200	1.599	2.734	13.702
coarea	1,458	596.041	409.409	2	6,193
rugged	1,356	42.656	47.309	1.920	334.972
latitude	1,458	34.517	3.114	24.850	40.521
longitude	1,458	−87.404	7.030	−106.235	−75.334
elevation	1,434	0.239	0.247	0.001	1.361
stability	1,459	0.142	0.360	0.000	3.152
avg_prec61_90	1,434	96.795	22.311	18.918	154.229
avg_temp61_90	1,434	15.828	2.996	8.789	23.737
Hill.Burton.Funds	1,148	19,432,599.000	96,399,662.000	632	1,725,654,322
cottonsuit	1,382	0.447	0.169	0.002	0.921
lynchrate	1,419	0.0001	0.0002	0.000	0.002
fbprop1860	1,341	0.013	0.031	0.000	0.262
FSSNAPBenefitfor3personfam	1,459	497.000	0.000	497	497
StateEITCRate	1,459	0.024	0.065	0.000	0.250
RefundableStateEITC1Yes	1,459	0.060	0.238	0	1

Note: Summary statistics of the variables used in the study.