Racial inequality in the U.S. unemployment insurance system

Daphné Skandalis[*], Ioana Marinescu[†], Maxim Massenkoff[‡]

April 28, 2022

[Please do not circulate.]

Abstract

While unemployment insurance (UI) could help attenuate racial income disparities in the U.S., Black unemployed workers seem to receive less UI benefits than White ones. To understand why, we analyze administrative data from random audits on UI claims in all U.S. states. We first document a large racial gap in the UI that unemployed workers receive after filing a new claim: Black claimants receive a 18.28% (6.51ppt) lower replacement rate (i.e. benefits relative to prior wage) than White claimants. In principle, the replacement rate of each claimant mechanically depends on her work history (e.g. the earnings before job loss or the reason for separation from prior employer) and on the rules prevailing in her state. Since we observe claimants' UI-relevant work history and state, we are in a unique position to decompose the causes of the racial gap among UI claimants. First, we show that racial differences in work history prior to unemployment create a 10.16% gap (3.62ppt); second, differences in rules across states create an 8.45% gap (3.01ppt); finally, we find no residual racial gap, once we account for state rules and work history differences. Thus, the decentralized design of the UI system generates new gaps in income between Black and White claimants, even when they have the same work history. Our results highlight that, even in the absence of individual discrimination, institutions can perpetuate racial inequality.

---

[*]University of Copenhagen, daphne.skandalis@econ.ku.dk. We thank for their help with accessing and understanding various datasets and/or for their feedback Antoine Bertheau, Ellora Derenoncourt, Eliza Forsythe, Nicole Fortin, Alix Gould-Werth, Peter Ganong, Nikolaj Harmon, Patrick Kline, Per Krusell, Camille Landais, Pauline Leung, Bruce Meyer, Robert Moffitt, Suresh Naidu, Arash Nekoei, Matthew Notowidigdo, Luke Shaefer, Jakob Søgaard, Shu Lin Wee, Stephen Woodbury, the participants of the CREST-IZA workshop, the European Labor Symposium for Early Career Economists, the Seminars of IFS STICERD, SOFI, IIES, Cornell, Bank of Canada, University of British Columbia, Boston College, Harris School of Public Policy

[†]University of Pennsylvania & NBER, ioma@upenn.edu.

[‡]Naval Postgraduate School, maxim.massenkoff@nps.edu.

1 Introduction

In the U.S., there are large and persistent racial income disparities. While social insurance and income-based redistribution programs could help alleviate these disparities, Black people facing economic difficulties are less likely than White ones to access these programs in many cases.[1] In particular, Black unemployed workers are less likely than White workers to benefit from unemployment insurance (UI), the main source of income during unemployment (e.g., Nichols and Simms, 2012; Gould-Werth and Shaefer, 2012). Yet, Black workers stand to gain the most from UI, as they hold little liquid wealth to smooth their consumption and face more difficulties finding new jobs due to racial discrimination in hiring (Ganong et al., 2021; Kline, Rose, and Walters, 2021). Here, we focus on unemployment insurance claimants, for whom we have excellent administrative data. Where is the racial gap in unemployment insurance coming from? Would a reform in the design of the unemployment insurance system reduce the gap? Factors outside of the UI system might contribute to this Black-White gap in unemployment insurance: Black workers may have a less favorable work history at the time when they lose their job (e.g. lower earnings in the preceding quarters, or voluntary separation from the last employer), which would undermine their eligibility for UI. But the design of the decentralized UI system might also play a role: because UI rules are systematically less generous in the states with a larger Black population (Figure 1), Black workers may receive lower unemployment insurance, even if they claim with the same work history as White claimants. Finally, Black workers might also experience discrimination in the treatment of their UI claim. How much does each of these channels contribute to the racial gap in unemployment insurance?

Identifying the sources of the racial gap in UI presents two key data challenges: first, administrative data on UI is collected separately in each state and not consolidated at the federal level; second, the aspects of individual work history that are relevant for UI (such as the earnings during the base period, or the reason for separation from the prior employer) are hard to re-construct from non-administrative data (Anderson and Meyer (1997)). In this paper, we exploit administrative data from audits of UI claims mandated by the federal Benefits Accuracy Measurement program (BAM) of the Department of Labor. This data covers all U.S. states, and contains all work history variables that enter the determination of unemployment insurance rights, as well as rich demographic information on claimants. Importantly, the claims to be audited are randomly sampled, allowing for inference on the general population. The BAM program mandates all states to conduct audits among paid and denied claims since 2002. Unlike prior research using the BAM data, we analyze not only audits of paid claims, but also those of denied claims. Combining these data allows

[1] States with a larger Black population provide less Temporary Assistance for Needy Families (TANF) welfare transfers to poor families (see e.g. Parolin (2021)). Historically, the exclusion of certain occupations from the Minimum Wage regulation (Derenoncourt and Montialoux, 2021), or from Unemployment Insurance (Lovell, 2002) also generated racial gaps in coverage.

us to construct a representative sample of all UI claimants for the entire U.S, from 2002 to 2018—the first to our knowledge. This is key for this paper, as it allows us to both study the racial gap in the unemployment insurance received by eligible claimants (i.e. the intensive margin), and the gap in UI eligibility (i.e. the extensive margin). We check the validity of our data construction by replicating with our data aggregate statistics on new claims from the Department of Labor.

We first document that states with a larger Black population have rules for unemployment insurance that are systematically stricter: the eligibility requirements are tougher, the cap on the weekly benefits eligible claimants can receive is lower, etc. We then provide new descriptive statistics on the claiming process: strikingly, we show that as many as 28% of new claimants are found ineligible. The replacement rate is 47% among eligible workers, but drops to 34% when accounting for denied claimants who don't receive any benefits. This finding of a high denial rate for new claims indicates that potential claimants face high uncertainty when deciding whether to claim. Most importantly, we find a large racial gap in the outcome of claims. The eligibility rate is 61% for Black claimants, and 76% for white claimants. Overall, Black claimants receive a 29% replacement rate when accounting for denials, while the replacement rate is 36% for White claimants: their replacement rate is 18.28% lower than that of White claimants. The rest of the paper explores where this racial gap in claimants' replacement rate is coming from.

We analyze the determinants of the gap in the unemployment benefits that Black and White claimants receive. We decompose this gap into three factors: differences in individual work history, differences in the rules prevailing where the claimant lives, and residual discrimination. We can credibly isolate the contribution of each factor, given that we observe virtually all variables that should be used to determine claimants' eligibility and benefits amount, according to UI rules: earnings during the base period, earnings during the highest quarter, number of weeks worked during the base period, the reason for separation. We estimate the state rule parameters for each state, by regressing UI outcomes on the interaction of work history variables and state indicators, for the sample of White claimants only. We then use a Oaxaca-Blinder style decomposition of the Black-White gap into differences in work history, differences in state rules, and residual discrimination. For a small number of claimants, some of the UI relevant characteristics are missing. We impute the missing values based on claimants' other characteristics, such as age, gender, race, prior occupation, prior industry and prior wage. We conduct various robustness checks to show that our results are not sensitive to the use of imputed variables.

Why do Black UI claimants receive a 18.28% lower replacement rate than White claimants? We find that racial differences in work history cause a 10.16% gap, accounting for a little over half of the difference. Though the gap explained by work history differences is large, it is striking that a large part of the racial gap in UI is *not* explained by differences in work history. This implies that the UI system generates large racial disparities in replacement rates between claimants with the same work history. Where is this inequality coming from? Our decomposition shows that differences in state-specific rules cause Black claimants to have a 8.45% lower replacement rate than White claimants. This finding highlights that institutions play a key role in generating racial inequality: the design of the decentralized UI system directly generates new gaps in income between Black and White claimants, even when they have the same work history. Finally, we find no residual racial gap once we account for state rules and work history differences. Perhaps surprisingly, this result indicates that the racial gap in UI does not appear to be caused by discrimination by UI officers against Black claimants in the implementation of the UI rules. In terms of policy, our results suggest that addressing racial inequality in unemployment insurance would require a reform of the institution towards more harmonization of state rules, rather than more monitoring of UI officers' behavior.

We then analyze separately the extensive margin—i.e. gap in eligibility—and the extensive margin—i.e. gap in replacement rate for eligible claimants. Black claimants are 18.8% less likely to be eligible. Half of this is due to state-specific rules, while the other half is explained by work history, again with no unexplained component. When eligible, Black claimants have the same replacement rate as White claimants, but this masks differences of treatment across states. In the UI system, eligible claimants with higher prior earnings receive a lower replacement rate due to a cap on the weekly benefit amount. Since eligible Blacks tend to have lower earnings, they should hence receive a higher replacement rate. In fact, differences in state rules generate a 2.97% Black-White gap in replacement rate among eligible claimants, which turns out to fully offset the effect of the progressivity of the UI system. Overall, this analysis shows that differences in state rules generate racial inequality in both the extensive and the intensive margin of UI, with the extensive margin being quantitatively more important.

Additionally, we examine another potential source of inequality in the UI system. UI officers could be racially biased in the way they measure work history variables—even if they don't appear biased in the way they attribute UI given claimants' measured work history. The BAM data offer a direct way to test for such a bias, to the extent that BAM auditors are less biased against Blacks than UI officers: we can compare the work history variables measured by UI officers, to those measured by BAM officers at the end of their audit. We test if UI officers tend to make mistakes (relative to BAM auditors) that are more favorable to White than Black claimants. We find no evidence of a systematic bias against Black claimants during the work history assessment. This confirms the idea that racial inequality in unemployment insurance in not produced by individual discriminatory behavior in the UI system, but is built into the design of the institution.

We discuss policy implications. As we find that the Black-White gap in UI for claimants with the same work history is primarily caused by the differences in rules across states, this gap would mechanically disappear if all states had the same UI rules. But if only one aspect of state rules were harmonized, how much would it reduce racial inequality? We discuss the effect of harmonizing two types of rules: those concerning the computation of benefits levels, and those concerning the eligibility requirements. We find that harmonizing eligibility requirements is the best option if one wants to both reduce racial inequality in the UI system, and increase the generosity of the UI system for low-earnings workers. For instance, setting a federal maximum for the Base Period Earnings required for eligibility, even as high as around \$3000 (corresponding to the third quartile of the distribution) would already decrease the racial gap in replacement rate explained by state rule differences from 8.4% to 7.2%, and the overall racial gap from 18.8% to 13%. This would be associated with an overall increase in replacement rate for lower-earning claimants, with only a small increase in costs (below 5%).

Finally, we discuss how our findings of how differences in state rules generate racial gaps for UI claimants generalize to the population of all unemployed. Specifically, we ask: would the differences in state rules generate similar gaps if all unemployed workers claimed UI? To answer this question, we compare the population of unemployed workers in the Current Population Survey and the population of claimants in our BAM administrative data. We find that the two populations are similar in some key dimensions, in particular in the extent to which Black people tend to live in stringent states. We thereby provides evidence that state rule differences would cause a similar racial gap in UI in the population of all unemployed workers if they all claimed UI.

Our findings contribute to the vast literature on racial inequality in economic outcomes. We are in the unique position to highlight the role of *institutions*: in most cases, it is difficult to disentangle institutional factors from pre-determined inequalities (work history in our example), and from individuals' discriminating behavior. In the setting of unemployment insurance, institutional rules determine benefit calculation based on work history, and we have the necessary data on work history. This allows us to show that the design of the UI system generates unequal insurance coverage for claimants with the same work history—without involving any discriminatory behavior. Historically, the economic literature might have underappreciated the importance of institutions due to its focus on intentional discrimination by individuals (Small and Pager, 2020). We are contributing to a recent strand of articles highlighting how the design of rules in other institutions creates of racial inequality.[2] In particular, Derenoncourt and Montialoux (2021) show that occupational exclusions from the federal minimum wage instated in 1938 contributed to the racial wage disparities in the following decades, which were attenuated by the minimum wage extensions in the 1960s. While it is beyond the scope of our paper to analyze why

[2]Aaronson, Hartley, and Mazumder (2021) show that the "redlining" maps produced by the Home Owners Loan Corporation (HOLC) federal organization in the 1930s contributed to subsequent racial inequality, in particular in home ownership. In the criminal justice system, Rose (2021) shows how the rules for convicted offenders on probation, though ostensibly race-neutral, generate racial disparities in incarceration.

states exhibit these specific differences in generosity in the UI system, we note that our results are consistent with the idea that racial diversity tends to prevent the enactment of generous social policies (Alesina, Glaeser, and Sacerdote, 2001).[3]

Second, our paper contributes to the understanding of the determinants of unemployment insurance recipiency. A large literature has investigated why UI recipiency is low in the U.S. and in other contexts (Blank and Card (1991),Anderson and Meyer (1997), Shaefer (2010),Fontaine and Kettemann (2019),Auray, Fuller, and Lkhagvasuren (2019), Blasco and Fontaine (2021),Lachowska, Sorkin, and Woodbury (2021)). Two types of factors can play a role: first, many unemployed workers might not be eligible given the requirements in place; second, the claiming rate of (likely) eligible unemployed workers has been found to be surprising low. Our main contribution to this literature is to explain why Black workers receive less UI than White workers in the U.S. This racial gap in UI recipiency had long been observed across survey data, but remained unexplained.[4] We show that racial differences in eligibility rates are very large, due to racial differences in both work history and state rules. In contrast, we provide suggestive evidence that racial differences in claiming behavior are limited.

Third, our paper is related to the literature on the design of unemployment insurance. Many studies have investigated which level of UI generosity—typically concerning benefits duration, or benefits level—can provide the maximum consumption smoothing for the lowest cost, to the average worker (e.g., Schmieder and von Watcher (2016)). In this paper, we show how the design of unemployment insurance affects disparities in the unemployment insurance received across workers. We find that decreasing the eligibility requirements in strict states is the most cost-effective way to both decrease racial inequality and increase UI coverage for low-wage workers. These results connect our paper to a recent strand of literature focusing on the welfare impact of reforms of UI eligibility rules (Leung and O'Leary (2020), de Souza and Luduvice (2020), Chao (2022)).

[3]This hypothesis is consistent with research on racial diversity and punitiveness in criminal justice (Feigenberg and Miller, 2021), and work highlighting the link between racial and welfare attitudes in public opinion (e.g. Gilens (2000), Alesina, Ferroni, and Stantcheva (2021)). It is also consistent with historians' finding of the important role of race in U.S. welfare state development (Lieberman (2001a),Katznelson (2006)).

[4]Various descriptive studies have established that black workers receive lower UI benefits: Lovell (2002), Nichols and Simms (2012), Kuka and Stuart (2021) use the SIPP; Gould-Werth and Shaefer (2012) use the unemployment insurance non-filers supplement of the CPS, O'Leary, Spriggs, and Wandner (2022) use the US Department of Labor Data on the characteristics of UI recipients. Latimer (2003) uses data from the unemployment insurance system in West Virginia in 1997 and document that black workers are less likely to qualify for UI for all categories of reasons (monetary, separation, non-separation). Grant-Thomas (2011) also provides suggestive evidence that Black workers might be more likely to receive an improper denial for monetary reasons.

2 Institutional context

2.1 Unemployment insurance in the US

In the United States, when workers lose their jobs, they can receive weekly unemployment benefits if they satisfy certain eligibility criteria. For those eligible, the average replacement rate (benefit amount divided by past earnings) is around 50 percent and the typical maximum duration is 26 weeks. Eligibility and weekly benefits amounts are determined based on individual labor market characteristics and on UI rules, which vary across states.

Eligibility To receive benefits, UI applicants must meet two broad eligibility criteria (USDOL, 2019). First, they must satisfy "monetary eligibility" criteria, meant to ensure a certain level of labor force attachment, which is relatively straightforward to verify through the state's quarterly wage records. Claimants must have sufficient Base Period Earnings, i.e. the sum of insured wages (i.e., wages subject to payroll taxes) in the last four quarters at the date of application. Some states also consider Highest Quarter Earnings, i.e. the earnings received during the highest quarter of the base period. For instance, claimant's total Base Period Earnings might have to surpass a certain multiple of the Highest Quarter Earnings. A few states use employment duration requirements: the weeks worked during the base period must exceed a certain threshold.

Second, they must also satisfy non-monetary criteria. The"separation" eligibility criteria requires that the last employment separation was involuntary. Typical reasons for separation are: voluntary quit, lack of work, and discharge. Generally, workers are considered eligible if they separated due to lack of work. In some cases, individuals with a voluntary separation meet non-monetary requirements if the separation is considered in good cause, such as to avoid harassment or domestic violence, or to relocate to another state because of a spouse's employment. The "non-separation" (or "other") eligibility criteria requires that the claimant is able and available to work. In practice, this non-separation criterion is less relevant for initial claims, which are the focus of this paper. After the initial eligibility has been determined, claimants must keep filing continuing claims every one or two weeks. At any point, new determinations can be made and continuing claimants may lose eligibility or receive a penalty if, for example, they earn too much income or do not search for work. Non-separation denials mostly concern such continuing claims.

Benefit amount The Weekly Benefit Amount is a non-linear function of the person's earnings during the base period. The general principle is that the Weekly Benefits Amount is set around 50% of prior weekly earnings, but the measure of prior earnings differs across states. The most common formula calculates benefits as a fraction of Highest Quarter Earnings. Alternatively, it is calculated as a fraction of Base Period Earnings, and, in a few cases, as a fraction of the average weekly wage during the base period. In most states, the multiplicative term is the same for all levels of earnings, but in a few states it is set higher for workers with lower earnings.

States impose caps on Weekly Benefit Amounts, which means that eligible claimants with high prior earnings mechanically receive a lower effective replacement rate. These caps are very low in many states, and are binding for as many as one third of UI recipients. In practice, these caps hence considerably reduce the effective replacement rates, and are also an important source of progressivity within the UI system (among eligible claimants). States also have a statutory minimum Weekly Benefit Amount, which increases the benefit amount for eligible claimants with low earnings. In practice, these minima do not importantly affect the amount of WBA received, as they are set so low that they are binding for very few UI recipients.

Differences across states Since its inception with the Social Security Act of 1935, the US unemployment insurance system has been unique in its level of decentralization, operating as a federal-state partnership (Baicker, Goldin, and Katz, 2007). Apart from certain national guidelines outlined in the original legislation, states can determine benefit amounts, duration, and eligibility requirements. In practice, states have used this discretion; most aspects of UI rules differ widely from state to state. This means that otherwise identical claimants from different states may differ in their eligibility to collect benefits and the level of benefits they are entitled to if eligible.[5]

2.2 The Benefit Accuracy Measurement (BAM) audit program

The Benefit Accuracy Measurement (BAM) system (formerly Quality Control) is how the Department of Labor tracks the accuracy of UI payments.[6] Since 1987, all states have been required by the DOL to conduct weekly audits on paid claims. In 2001, this was extended to include denied claims (i.e. claims that received disqualifying ineligibility determinations). The key quality control metrics include paid claims accuracy and denied claims accuracy.[7] Note that we start using denied claims in 2002 as they were relatively few audits conducted in 2001.

The claims to be audited are selected following a pre-defined sampling procedure, designed to obtain a representative sample of ongoing claims. Paid claims selected for an audit are sampled from the stock of accepted claims associated with a UI payment in that

[5]This fact was noticed early on in the program's inception. For instance Reticker (1942) writes, "So long as State unemployment compensation laws differ in the fractions of wages available as weekly or annual benefits, in minimum and maximum weekly benefit amounts, in methods of rounding, and in uniform and maximum duration, there will be disparity in benefits available under the State laws for claimants with identical wage records" (p 11).

[6]Woodbury (2002) provides an overview of the BAM program. For other research using BAM data, see, e.g., Ebenstein and Stange (2010) and Ferraro et al. (2020).

[7]A recent annual report is available at this link: `https://oui.doleta.gov/unemploy/bam/2019/IPIA_2019_Benefit_Accuracy_Measurement_Annual_Report.pdf`.

week. Denied claims selected for an audit are sampled from the stock of claims that received a negative determination in that week. Overall, claims to be audited are selected randomly within each state, week, and claim type (the four claim types are: paid, monetary denials, separation denials, and other denials). Information on the count of claims in the population, for each state, week, and claim type is recorded, such that the probability to be selected for each ongoing claim can be computed. Auditors must then collect information on all claimants selected for an audit, using all necessary channels: they systematically ask claimants to fill standardized questionnaires, and then collect complementary information through investigative processes when necessary: employer interviews; third-party verifications, income verifications, etc.

3 Data

3.1 Construction of the study dataset

We collected paid and denied audited claims from the Benefit Accuracy Measurement (BAM) (Woodbury, 2002; Woodbury and Vroman, 2000) for the years 2002-2017. Together, the paid and denied claim audits can be used to construct random samples from the population of new applicants, since all applicants to UI should end up either paid or denied—in other words, at risk of being audited under one of the two programs.[8] In order to make our sample representative of new claimants, we make some sample restrictions. Both the paid claims and denied claims audits contain continuing claimants—those who have already received their first payment. We restrict our sample to payments corresponding to the first compensated week for paid claims, and denials of new claims for denied claims. We do not include additional claims or re-opened claims. This leads to a sample of about 200,000 observations. To make our sample representative of all new claimants, we build weights equal to the inverse of the probability that a new claim is included in our sample: for each state s, week t and claim type c, the probability of being in our study sample corresponds to $\frac{\#AuditAll_{cst}}{\#PopAll_{cst}}$, i.e., the size of the audit sample over the size of the population of ongoing claims.

To validate our data construction, we compare statistics obtained from our study dataset to the closest available statistics from the Department of Labor. We use our data to compute the implied count of all new claims, paid new claims, denied new claims, and the denial rate among new claims. Statistics for similar measures are available by quarter and state in the DOL table ETA 5159. We find that our measures and the DOL measures align very closely (Figure A.1). We also compare the composition of paid claimants in the BAM sample to that of continuing claimants, available in the Department of Labor's ETA 203

[8] In practice, the status of claims can also be pending for some time, but we consider that this is negligible in our main analysis. The comparison of our study dataset with the aggregate statistics from the DOL indicates it is a very reasonable assumption.

report ("Characteristics of the Insured Unemployed"). Table A.1 reports demographic proportions from both datasets: the two sources align closely. For more details, see Appendix A.2.

3.2 Information on claimants

Claimants characteristics The BAM data includes rich information on the characteristics of claimants. First, the BAM data contains a rich set of individual variables that are a priori not relevant for UI determinations, and are collected for statistical purposes[9]: demographic characteristics (including race and ethnicity), wage in prior occupation, prior occupation, prior industry. The information on race and ethnicity is collected like in the US Census: claimants have to choose one race category (White, Black or African American, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific, Islander, Multiple Categories Reported, Race Unknown) and separately report their ethnicity (Hispanic, Not Hispanic, Unknown). In our main analysis, we compare the UI outcomes of claimants who report being Black to those who report being White. In robustness analyses, we compare non-Hispanic Blacks and Hispanics to non-Hispanic Whites, as it is common to treat Hispanics separately.[10]

Claimants' work history Second, the BAM data contains the work history variables relevant for UI determinations: Base Period Earnings, Highest Quarter Earnings in base period, the ratio of the Highest Quarter Earnings over all Base Period Earnings, Weeks Worked in base period, reason for separation. These variables are reported twice: as they were reported to the auditor initially, and as they are evaluated by the auditor at the end of the audit. In our main analysis, we use the pre-audit variables. In additional analyses, we test if the difference between pre- and post-audit variables is correlated with race.

We observe all work history variables for paid claims. For denied claims, we only observe the work history variables that correspond to the reason for the denial (monetary or non-monetary). Indeed, for each claim, the dataset only contains the work history variables relevant for the auditor: for paid claimants, auditors examine everything ; for monetary denied claims, they only examine the monetary determination (we observe monetary variables) ; for non-monetary denied claims, they only examine the corresponding non-monetary type of determination (we observe non-monetary variables). In a part of the paper, we focus on the racial gap in *monetary determinations*, using the sample of claimants that are eligible or monetary-denied. In that case, we observe all the relevant work history variables

[9]Note that this information is also collected for statistical purposes by UI officers for all claimants, independent of the audit process, as the Department of Labor issues statistics on claim counts by demographics (ETA 203 "Characteristics of the Insured Unemployed" reports).

[10]In most publications based on Current Population Survey (CPS) data, the Bureau of Labor Statistics includes respondents of Hispanic ethnicity within the race groups (White, Black or African American, Asian) in addition to showing them separately.

(i.e. all monetary variables). In another part of the paper, we analyze *all determinations* in the full sample of claims, using proxies for work history variables. Indeed, we are in a unique position to build proxies, given that for large subsets of our sample, we observe work history variables together many other claimants' characteristics: prior wage, gender, age, occupation, industry, ethnicity and race (for more details, see Appendix A.3).

Last, a second minor data limitation affects a small fraction of the claims with a monetary determination (i.e. paid or monetary-denied claims). We don't observe the Highest Quarter Earnings in the state-months that do not use this variable in their UI determinations. This corresponds to 10% of monetary determinations in our sample. For our monetary determinations analysis, we hence restrict our sample to the 90% of claims in state-months which use the standard set of monetary variables when we analyze monetary determinations: for these claims, we observe all relevant work history variables (i.e. Base Period Earnings, Highest Quarter Earnings and the percentage of earnings during the highest quarter).[11]

Unemployment insurance outcomes Finally, the BAM data contains information on UI outcomes: the eligibility status, Weekly Benefit Amount, potential Weekly Benefit Amount (i.e. Weekly Benefit Amount that a claimant would have received if she was monetary eligible). These variables are also reported before and after the audit: discrepancies between these values indicate that the assessment of the claimants' case has changed in light of new information. In addition to these variables, we construct a measure of the replacement rate, to more directly quantify the insurance against income loss provided by the UI system. We measure the replacement rate by taking the ratio of Weekly Benefits Amount over 40×Prior Hourly Wage, following the Department of Labor's definition.[12] In robustness checks, we also consider alternative measures: 52×Weekly Benefits Amount over Base Period Earnings or 13 ×Weekly Benefits Amount over Highest Quarter Earnings.

3.3 Comparison with other data sources in the literature

While many papers discuss claiming behavior, data on UI claimants are scarce. We have constructed our dataset from combined audits data to provide rich information on a representative sample of new UI claimants. The data provides a unique opportunity to describe the traits of people who claim UI, and the typical outcomes from these applications across all US states. To our knowledge, only three other types of data sources allow obtaining descriptive statistics on UI claimants, and each presents important limitations. First, the

[11]Note that none of these 90% state-months use the number of Weeks Worked during the base period in their monetary determination. Consequently, even if we don't observe this variable in this subsample, it is not a problem: we only need to control for the variables that affect UI outcomes for at least some claimants in the considered sample.

[12]See `https://oui.doleta.gov/unemploy/ui_replacement_rates.asp`

CPS Non-Filer supplements have been specifically designed to document UI claiming behavior among workers who are unemployed or marginally attached to the labor force (see e.g. Gould-Werth and Shaefer (2012)). But these surveys have been infrequent and their sample size is small. Moreover, they only collect imprecise information on the work history variables relevant for UI determinations—which is crucial for the main analyses of our paper. Second, administrative UI claims state records matched with wage records contain rich information on work history variables and UI outcomes for all claimants in the state (see eg Lachowska, Sorkin, and Woodbury (2021)). But these data are at the state level, and have never been consolidated for all of the U.S. to our knowledge. Additionally, these UI claim records do not necessarily contain demographic information for all claimants, such as information on race. Third, several papers have indirectly backed out information on UI claimants from information on UI recipients, as data on UI recipients have been relatively less scarce. In particular, the Survey of Income and Program Participation (SIPP) inquires about UI receipt. This approach—used eg by Blank and Card (1991), Anderson and Meyer (1997), Kuka and Stuart (2021)—consists in analyzing UI receipt among likely eligible unemployed workers to infer information on the selection of likely eligible claimants. It is however very sensitive to the definition of likely unemployed workers.

4 Empirical strategy

Our objective is to document the raw gap in UI between Black and White claimants in the U.S. and to identify where it comes from. In this section, we first formally define the different components of the racial gap that we want to measure, then explain our estimation method, and finally discuss the underlying identifying assumptions.

4.1 Decomposition of the racial gap in UI receipt

The determinants of UI In principle, UI outcomes are directly a function work history variables in each state. State rules change the impact of work history variable on outcomes, and not just by adding a fixed term. Let's define UI_i^*, the statutory UI outcome that claimant i should receive based on her work history characteristics X_i, according to the rules in her state. In a linear model, statutory UI outcomes for claimants in state k can be expressed as the sum of a fixed term $\alpha_{0,k}$ and of the effect of worker characteristics given the local rules $X_i\alpha_{1,k}$, such as:

$$UI^*_{i,k} = \alpha_{0,k} + X_i\alpha_{1,k} \tag{1}$$

where the α coefficients can be interpreted as representing the rules in the UI system. We recover these coefficients by estimating model 1 for each state, which amounts to reverse-engineering the UI state rules from the data. We provide more details on this estimation step in section 4.2 .

Let's define the parameters of the average rule across states: $\overline{\alpha}_0 = \sum_k \overline{S_k} \cdot \alpha_{0,k}$, and $\overline{\alpha}_1 = \sum_k \overline{S_k} \cdot \alpha_{1,k}$, where $\overline{S_k}$ is the fraction of claimants who are in state k. $\overline{\alpha}_0$ and $\overline{\alpha}_0$ are thus coefficients weighted by the share of each state in the overall US claimant population. We can express the statutory outcome of claimant i in state k as:

$$UI_i^* = \sum_k S_{i,k} \cdot UI_{i,k}^* = \overline{\alpha}_0 + X_i \cdot \overline{\alpha}_1 + \sum_k \left(S_{i,k} \cdot \widetilde{\alpha}_{0,k} + S_{i,k} \cdot X_i \cdot \widetilde{\alpha}_{1,k} \right) \tag{2}$$

where $S_{i,k}$ is an indicator for claimant i living in state k, $\widetilde{\alpha}_{1,k} = \alpha_{1,k} - \overline{\alpha}_1$ and $\widetilde{\alpha}_{0,k} = \alpha_{0,k} - \overline{\alpha}_0$. The coefficients $\widetilde{\alpha}_{0,k}$ and $\widetilde{\alpha}_{1,k}$ capture how the rule in state k departs from the average rule: when they are negative, the state is less generous than average ; when they are positive, the state is more generous than average. If the $\widetilde{\alpha}$ coefficients were equal to zero for all states, then there would be no differences in rules across states. One can interpret $\overline{\alpha}_0 + X_i \cdot \overline{\alpha}_1$ as the average UI outcome for a worker with characteristics X_i, i.e. the outcome that this worker would obtain in the average state (weighted by claimant share). $S_{i,k} \cdot X_i \cdot \widetilde{\alpha}_{1,k}$ is the state-specific additional effect of worker characteristics, and $S_{i,k} \cdot \widetilde{\alpha}_{0,k}$ is the state-specific additional level shift allowing some states to be overall more generous. Depending on whether state k is more or less generous than average for workers with characteristics X_i, these additional state-specific terms may add or subtract from the average UI outcome $\overline{\alpha}_0 + X_i \cdot \overline{\alpha}_1$.

The components of the racial gap in UI From equation 2, we can express the average of statutory outcomes for black and white claimants, $\overline{UI_g^*}$, where $g \in \{b, w\}$ denotes the race group index (Black or White). We present these derivations step by step in Appendix B.1. The gap between the average statutory outcomes UI^* for Black and White claimants can be written as:

$$\overline{UI_b^*} - \overline{UI_w^*} = (\overline{X_b} - \overline{X_w})\overline{\alpha}_1 + \sum_k \left((\overline{S_{b,k}} \cdot \overline{X_{b,k}} - \overline{S_{w,k}} \cdot \overline{X_{w,k}}) \cdot \widetilde{\alpha}_{1,k} + (\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot \widetilde{\alpha}_{0,k} \right) \tag{3}$$

where $\overline{X_g}$ represents the average work history characteristics for each group overall nationally, $\overline{X_{g,k}}$ the average work history characteristics for each group in state k, and $\overline{S_{g,k}}$ represents the fraction of each group who lives in state k (e.g. share of all Black UI claimants who live in Pennsylvania).

We can hence decompose the "raw" gap in the average observed UI outcomes of Black and White claimants, $\overline{UI_b} - \overline{UI_w}$, into the following components:

- The gap explained by *differences in the work history variables* of black and white claimants at the national level: $(\overline{X_b} - \overline{X_w}) \cdot \overline{\alpha}_1$. This captures the part of the racial gap in unemployment benefits that would exist due to their differences in work history, if all claimants were exposed to the same rule, which we define as the average of state rules, i.e. $\overline{\alpha}_1$.

- The gap explained by *differences in UI rules across states*: $\sum_k \Big((\overline{S_{b,k}} \cdot \overline{X_{b,k}} - \overline{S_{w,k}} \cdot \overline{X_{w,k}}) \cdot \widetilde{\alpha}_{1,k} + (\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot \widetilde{\alpha}_{0,k} \Big)$. This gap would be eliminated if UI rules were the same across states, i.e. if $\widetilde{\alpha}_{0,k} = \widetilde{\alpha}_{1,k} = 0$.

- The gap *unexplained by work history variables and state rules*: $(\overline{UI_B} - \overline{UI_W}) - (\overline{UI^*_B} - \overline{UI^*_W})$. If UI rules are strictly applied, this gap should be zero. If it is different from zero, this is suggestive of discrimination in the implementation of UI rules in each state.

Interpretation of the gap explained by state rules differences Differences in UI rules across states do not necessarily create a racial gap that disadvantages Black claimants. Under what conditions do state rules create such a gap? To help answer this question, we rewrite the gap explained by state rule differences in each state k from equation (3), as:

$$(\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot (\overline{X_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) + (\overline{X_{b,k}} - \overline{X_{w,k}}) \cdot \overline{S_{w,k}} \cdot \widetilde{\alpha}_{1,k} \tag{4}$$

The differences in UI rules across states can influence the gap in unemployment insurance through two channels. First, Blacks are disadvantaged when rules are stricter ($(\overline{X_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k})$ is negative) in states where a larger fraction of all Black claimants live relative to the fraction of all White claimants ($(\overline{S_{b,k}} - \overline{S_{w,k}})$ is positive). Second, Blacks are disadvantaged when the impact of work history characteristics is larger ($\widetilde{\alpha}_{1,k}$ is positive) in states where they have worse work history characteristics than White claimants ($(\overline{X_{b,k}} - \overline{X_{w,k}})$ is negative).[13] In our descriptive analysis, we will provide new evidence that Black claimants are indeed less likely to live in generous states, and also that they tend to have particularly unfavorable work history characteristics in states with a large premium on these characteristics.

4.2 Estimation of the components of the racial gap in UI receipt

We implement the decomposition of the racial gap for various UI outcomes. We start with analyzing the racial gap in the overall UI generosity for eligible and denied claimants together, coding UI outcomes as 0 for those denied. We measure UI generosity using both the Weekly Benefit Amount, and the replacement rate: while the Weekly Benefit Amount is the outcome that is directly determined by UI rules, the replacement rate is the more economically relevant outcome, as it measures how much insurance against income loss is

[13] Note that even if Black claimants had the same work history composition as White claimants at the national level, they could still have different compositions in some states.

provided by the UI system.[14] We then distinguish the extensive and the intensive margin. For each UI outcome, we estimate model (1) state by state, to recover the rule parameters $\alpha_{0,k}$ and $\alpha_{1,k}$, based on the observed relation between work history variables and the outcome. To estimate model (1), we restrict our sample to White UI claimants only, so that our estimates of the rule parameters cannot capture racial bias. White UI claimants are hence implicitly considered as treated neutrally. We include all the work history variables that are used in the determination of the considered outcome in at least some states. We enter control variables as flexibly as possible, to allow for non-linear relations: we discretize continuous variables, and include interactions. We then estimate the different components in model (3), based on estimated rule parameters $\hat{\alpha}_{0,k}$ and $\hat{\alpha}_{1,k}$ and the various sample means ($\overline{X_w}$, $\overline{X_{w,k}}$, $\overline{S_{w,k}}$, $\overline{X_b}$, $\overline{X_{b,k}}$, and $\overline{S_{b,k}}$). We use bootstrap to compute standard errors.

We vary the scope of our analysis: we first include all types of UI determinations (monetary and non-monetary), which offers the most comprehensive picture on the racial gap in UI, but requires using proxies for work history characteristics; we then focus on monetary determinations, which is the most important single type of determination and for which we can observe all relevant work history variables.

First approach: all types of UI determinations In our first—more general—approach, we use the full study sample. Our main estimates measure the gap in overall UI received by claimants. Then, when we focus on the extensive margin, we analyze racial differences in eligibility ; when we focus on the intensive margin, we analyze racial differences in UI generosity for eligible claimants. While both monetary and separation variables matter for claimants' eligibility, only monetary variables matter for the computation of the benefits among those eligible. Therefore, we only include monetary variables when we analyze the gap in UI generosity conditional on eligibility, and we include both monetary and separation otherwise. We use different measures of work history variables for those different analyses. For the analysis of the gap among all claimants, we use the proxies built from predicting work history variables based on claimants' prior wage, gender, age, occupation, industry, ethnicity and their interaction with race. In contrast, for the analysis of the gap among eligible claimants, we use the actual variables to measure Base Period Earnings, and we use proxies obtained from a richer set of variables to measure the other monetary variables (for more details, see Appendix A.3).

Second approach: monetary determinations In our second approach, we focus on monetary decisions. Our main estimates allow us to quantify the determinants of the gap in UI generosity arising from monetary determinations only, i.e. assuming that there are

[14] We measure the replacement rate by taking the ratio of Weekly Benefits Amount over $40\times$Prior Hourly Wage, following the Department of Labor's definition. Our results remain qualitatively similar when we use alternative measures (see Section 6.3)

no other eligibility criteria.[15] When we focus on the intensive margin, our estimates measure the determinants of racial differences in monetary eligibility ; when we focus on the extensive margin, our estimates measure the determinants of racial differences in the UI generosity that monetary eligible claimants might receive if they also satisfy non-monetary eligibility criteria. For this analysis, we restrict our sample to the 90% of observations in the state-months that use the standard set of variables to determine monetary eligibility. In these states, we observe all the relevant work history variables and do not need to use any proxies.

4.3 Identification assumptions and robustness checks

As highlighted by Fortin, Lemieux, and Firpo (2011), while decomposition analyses are often treated as pure accounting exercises, correctly attributing to various factors their contribution to population gaps relies on identifying assumptions, similar to those from the treatment effects literature. Our estimates identify the contribution of claimants' work history differences, and state rules differences to the racial gaps, if we do not omit relevant information that correlates with race when we estimate model (1). We could omit relevant information if we don't measure individual work history variables precisely enough, or if we don't allow for enough flexibility in the functional form that defines benefits as a function of work history variables. Our estimates would be biased if these omitted UI-relevant individual characteristics were correlated with race.

To address the concern that we omit relevant information correlated with race, we implement a series of tests and robustness checks. First, we re-estimate model (1) including the individual characteristics that should be irrelevant for UI determination: age, gender, education, occupation, industry. The idea is that if we did omit relevant information correlated with race, it would likely correlate with these observable variables. If our estimates of the different components of the racial gap remain stable when we add these controls, it suggests that there was no such omission.

Second, we test the sensitivity of our results to imputation of missing work history variables. In robustness checks, we focus on the 90% of states that use the same variables to compute the weekly benefit amount. In these states, we observe all relevant monetary work history variables. First, we focus on the gap among eligible claimants, and we show that we obtain identical estimates for the different components using our proxied or actual measures. Second, we focus on monetary eligibility (instead of focusing on all eligibility

[15]For this analysis, we re-weight observations so that our sample is representative of all monetary determinations, including those that were made for the non-monetary-denied claimants (who are excluded). By construction, all non-monetary-denied claimants are monetary-eligible. Therefore, we increase the weights of paid claimants to reflect the total weight of both paid claimants and non-monetary-denied claimants who where sampled in the same week, and the same state. This relies on the assumption that paid and non-monetary-denied claimants are comparable in their monetary characteristics. The results are unchanged if we do not implement this weights correction.

decisions) among claimants. We restrict our sample to claimants are who are either eligible or monetary-denied. We show that our results remain stable whether we use the proxied or actual monetary variables.

5 Descriptive statistics

5.1 Who claims UI?

In Table 1, we summarize the characteristics of all new claimants—both those who turn out to be eligible and those denied— (Column 1) and of new eligible claimants (Column 2), both based on our BAM dataset. Comparing the composition of claimants and that of eligible claimants allows inferring which categories are disproportionately more likely to have their claims rejected. Additionally, we present the characteristics of unemployed individuals from the CPS as a comparison (Column 3): by comparing the composition of claimants and that of the unemployed, we can determine which categories are over or under represented among claimants relative to the unemployed.

These statistics yield some novel findings. First, Blacks represent 19% of all UI claimants, while Whites represent 69% (Col 1). So Black and White claimants represent most of our sample, while other claimants are dispersed in various race categories. The proportion of Black claimants is lower among new eligible claimants and the proportion of White claimants is higher, indicating higher rejection rates for Black claimants (Col 2). Interestingly, the proportion of Blacks among new claimants is similar to that among unemployed workers. In contrast, White claimants are slightly under-represented among all claimants. We note that 5% of claimants in BAM declare their race is unknown while this is virtually never the case in the CPS, which suggests some classification differences. We see that UI claimants include 16% of Hispanics—which is a bit below their proportion in the unemployed population, and they have a slightly higher rejection rate than the other ethnic groups. 57% of UI claimants are men, which is a bit below their proportion in the unemployed population, but they appear to have a slightly lower rejection rate than women. Younger workers (age 24 and below) appear slightly under-represented in the claimants population and more likely to be rejected. High school graduates are also over-represented among claimants (they represent 42% of claimants versus 39% of unemployed), while workers with BAs or more are under-represented.

These data could be used to proxy the claiming rate in each demographic group, by taking the ratio of count of claimants from our dataset over the count of unemployed from the CPS. However, taking the ratio of population counts obtained from two different sources is not straightforward. For instance, the population of unemployed workers might be too broad as people tend to file new claims in the first months of their unemployment spell, or too narrow, as people can also claim when they are not classified as unemployed. However, we note that the finding that Whites are slightly under-represented among claimants while Blacks are not, suggests that the UI claiming rate of White workers might be slightly lower than that of Black workers. This might seem in contradiction with the findings of a higher claiming rate among White unemployed workers in the CPS non-filers supplement from 2005 (Gould-Werth and Shaefer, 2012). In fact, the comparison between the count of claimants from our data and the count of unemployed in the CPS also implies a higher claiming rate for Whites than for Blacks when we focus on the year 2005, as Gould-Werth and Shaefer (2012) did, instead of using data for the whole period 2002-2017. We further discuss claiming rates by race in Appendix Section A.4.

5.2 What is the outcome of claiming?

In Table 2, we show averages of UI outcomes such as the weekly benefit amount and replacement rate, along with the key work history variables used to determine benefit eligibility. We find that 28% of new claimants are found ineligible for UI: 13% of new claims are denied for a monetary reason, 11% are denied for a separation reason, and 4% for other reasons. This indicates that potential claimants face high uncertainty about the outcome of a claim, and rather low expected returns: the replacement rate is 47% among eligible, but drops to 34% when accounting for the denied claimants who don't receive any benefits. How do claiming outcomes vary by race? The raw statistics already indicate a racial gap in UI outcomes: for a Black claimant, the expected return is only a 29% replacement rate, while it ranges around 36% for a White claimant. This is driven by the large gap in eligibility rates: 75% of White claimants are considered eligible for benefits while only 62% of Black claimants are. This is similar to findings in Gould-Werth and Shaefer (2012), where 71% of White and 64% of Black applicants received UI. However, when we condition on eligibility, we find that there is no Black-White gap in replacement rate. We will show that this absence of a gap among eligible claimants comes from two opposing forces. On the one hand, Black eligible claimants tend to have a lower prior wage. As the UI system is progressive among eligible workers, this means that Blacks receive a relatively higher replacement rate than White eligible claimants, since White claimants have higher prior wages (see Section 2.1 for more details on progressivity in the UI system.). On the other hand, Black claimants live in less generous states. So they tend to receive a lower replacement rates than White eligible claimants living in more generous states. We note that this is consistent with Ganong et al. (2021) finding that Black and White workers experience the same relative income drop upon unemployment, conditional on receiving unemployment benefits.

Finally, the table shows differences across groups in UI-relevant work history variables. All the differences suggest that White workers will have higher weekly benefit amounts based on existing eligibility rules. Highest quarter earnings are 26% lower for Blacks, with an even larger gap in base period earnings, the sum of earnings over the most recent four-quarter period. Black claimants also tend to have worked fewer works and are less likely to have separated due to lack of work.

5.3 UI rules and claimants' characteristics across states

It has been long documented states with a larger Black population systematically have less generous UI rules (Lieberman, 2001b). We provide a first illustration in Figure 1: in the upper map, darker states are those with lower caps on Weekly Benefits Amount (relative to the average wage of claimants in that state). These states hence tend to offer less generous unemployment benefits to their residents. On the bottom map, dark states are those with a larger share of Black claimants. The comparison of these maps indicates that there is a negative spacial correlation between the importance of the Black population and UI generosity, at least as far as the cap on WBA is concerned. For example, Louisiana, where 52 percent of claimants are Black in our sample period, has seen its maximum weekly benefit amount drop from about 50 percent to 40 percent of the mean prior wage. Montana, in contrast, where just 1 percent of claimants are Black, had its maximum WBA average 70 percent of new claimant wages.

In Figure 2, we provide a precise quantification of the correlation between various measures of UI generosity and the share of Black claimants, weighting states by their number of claimants. We consider various dimensions of state rule generosity, such as the maximum WBA in the state. Additionally, we also use summarize all dimensions of UI generosity into one index, by taking the statutory Weekly Benefits Amount that a claimant with average work history characteristics should get in the state. Using the notations detailed in Section 4.1, this index can be expressed as: $\overline{X} \cdot \alpha_{1,k} + \alpha_{0,k}$. Panel (A) shows a clear negative correlation between the share of black claimants and the index of generosity of state UI rules. The typical weekly benefit amount decreases by \$9 for every 10 percentage point increase in the share of Black claimants. Panel (B) shows that the cap on weekly benefits (relative to the mean prior wage of claimants in the state) declines by 2.5 percentage points for each 10 percentage point increase in the share of Black claimants. Panel (C) shows that the replacement rate, calculated to capture the linear term in each state's UI benefit formula, falls by 0.4 percentage points with every 10 percentage point increase in share Black. In Panel (D), we analyze how frequently states grant eligibility to claimants who quit their prior job, which represents a dimension of discretion that states exercise at the stage of the eligibility determination. Again, this measure is negatively correlated with the share of Black claimants. Overall, the share of Black claimants is negatively correlated with all the considered dimensions of UI generosity. We provide further statistics on these measures of UI generosity, and on others, in Appendix Table C.1. We also present in Figure C.1 the correlation of state rule generosity with another measure of the over-representation of

Black claimants: instead of using the share of claimants in the state who are black, we take the difference between the fraction of black claimants located in the state and the fraction of white claimants located in the states, as this perhaps less intuitive measure more closely corresponds to the decomposition formula in equation 3. The conclusions remain the same.

State rules differences can also generate a racial gap in UI receipt, if states that give the highest premium for work history characteristics are those with the largest racial gap in work history characteristics. We hence also examine whether we observe a correlation between the premium on work history characteristics and work history gaps in Figure C.2. We measure this premium by taking an index, corresponding to the premium on her Weekly Benefits Amount that a claimant with average work history characteristics should receive in that state: $\overline{X} \cdot \alpha_{1,k}$ (notations explained in Section 4.1). To measure the racial gap in work history characteristics in each state, we successively analyze various dimensions of work history characteristics, such as the gap in base period earnings. And we also use an index summarizing all the work history characteristics relevant for UI, corresponding to the Weekly Benefits Amount that a claimant with these specific work history characteristics should receive given the average UI rules across states: $X_i \cdot \overline{\alpha}_1$. Overall, it appears from all panels in Figure C.2 that Black claimants tend to have a worse work history than White claimants in states that give a larger premium for work history (though the correlation is not always significant). This should amplify the gap in unemployment insurance generated by differences in state rules.

6 Main results: racial gaps in UI

6.1 The overall racial gap in UI

We present our decomposition of the Black-White raw gaps in unemployment insurance into three components: differences in individual work history (applying the same average UI rules to all claimants), differences in the rules prevailing where the claimant lives, and unexplained differences. The objective is twofold. First, we explain the causes behind the raw gaps. Second and perhaps most importantly, when subtracting the gaps explained by work history, we measure the size of the racial inequality in the UI system—to the extent that equality can be defined as claimants with the same work history receiving the same replacement rate.

The raw racial gap We present our main results in Table 3. The first line reports the estimates of the raw gaps between Black and White claimants, in various UI outcomes. On average, Black claimants receive a \$92.31 lower Weekly Benefits Amount (WBA) than White claimants (col (1)). To help assess the magnitude of this gap, the bottom part of the Table presents the gap relative to the average WBA for white claimants: Black claimants receive 33.61% lower benefits than White claimants. We then analyze the difference in replacement rate, rather than Weekly Benefits Amount: this provides a better measure of how UI insures against income loss. Black claimants receive a 6.51 percentage points lower replacement rate, which corresponds to a 18.28% gap relative to White claimants (col (2)). The gap in replacement rate is smaller than the gap in WBA. This is because Black claimants tend to have lower prior earnings (see the Table 2): their WBA is much lower, but as their prior earnings are also lower, their replacement rate, i.e. ratio of the two, is below that of White claimants by a smaller margin. The 18.28% gap in replacement rate implies that Black claimants are substantially less well insured through unemployment insurance against loss of income due to job loss than White claimants.

The overall Black-White gap in unemployment insurance receipt among claimants can reflect a gap in eligibility—the extensive margin—and a gap in unemployment insurance for eligible claimants—the intensive margin. We analyze these additional outcomes in Table 3 col. (3)-(5). Black claimants are 14.19 percentage points less likely to be found eligible, which corresponds to a 18.8% gap relative to White claimants (col (3)). When they are eligible, Black claimants receive a \$66.35 lower WBA, which represents a 18.25% gap (col (4)). Perhaps surprisingly, it turns out that Blacks' replacement rate conditional on being eligible is not significantly different from that of White claimants (col (5)). Here again, the gap in replacement rate among eligible claimants is smaller than the gap in WBA because of the racial gap in prior earnings: when they are eligible to unemployment insurance, Black recipients receive lower WBA – which reflects their lower earnings – but roughly the same replacement rate as White claimants.

The gap explained by state rules We decompose the raw gaps for each UI outcome into its three components in Table 3. We first report the gap explained by state rules differences (component (i)). Black claimants receive a 11.19% lower WBA (\$30.72) than White claimants due to differences in state rules (col (1)). Similarly, Black claimants receive a 8.45% (3.01ppt) lower replacement rate due to differences in state rules (col (2)). We then disentangle the effect of state rule differences on the extensive and the intensive margin of UI. State rule differences cause a 8.99% Black-White gap in the eligibility rate (Table 3, col (3)). Black claimants hence disproportionately end up receiving no unemployment insurance at all due to the stricter rules in their state, which plausibly entails large welfare costs. Moreover, state rule differences cause a 3.58 to 2.97% gap in the weekly benefits amount and the replacement rate received by the claimants who have been found eligible (col (4)-(5), third line of lower panel). These results indicate that state rules importantly affect both the extensive and the intensive margin of UI.

These estimates of the gaps explained by state rule differences carry our key findings. First, they show that state rules differences completely explain the raw gap in replacement rate. The comparison between the 18.28% raw gap in replacement rate (line 1, col (2)) and the 8.45% gap caused by state rules in (line 2, col (2)) indeed highlights that the cause of the raw gap in replacement rate is entirely institutional. Second, the finding of a large gap explained by state rule differences sheds light on the presence of *large racial inequality in the UI system*—when defining inequality as claimants with the same work history receiving different replacement rates. Indeed, Black claimants receive a 8.45% lower replacement rate just due to the fact that the rules prevailing in their states are stricter—independent of any difference in their work history. The decentralized UI system is unequal at all stages of the claiming process: it makes Black claimants less likely to be eligible for UI, and receive a lower replacement rate when they are eligible.

The gap explained by work history We then report the gap explained by work history differences (component (ii)). The gap in WBA driven by differences in claimants' work history is large: due to different work history, Black workers get 23.57% ($64.75) lower benefits than White workers (col (1)). In contrast to the gap in raw benefit levels (WBA), the gap in replacement rate explained by work history is smaller, and insignificant: 10.16% (3.62ppt) (col (2)). Why is that? Work history variables mainly include various measures of prior earnings, and prior earnings have opposite effects on replacement rates. On the one hand, Blacks' lower prior earnings decrease their chances of being eligible, relative to White claimants: specifically, racial differences in work history lead Black claimants to be 11.89% less likely to be eligible than White claimants (col (3), lower panel). On the other hand, eligible Whites' higher prior earnings are mechanically associated with a lower replacement rate, due to the cap on WBA. This means that, due to work history, *eligible* Black claimants' replacement rate is higher, and specifically it is higher by 4.24% (col (5), lower panel). To sum up, there isn't much of a racial gap in overall replacement rate due to work history because – based on work history – Blacks are less likely to be eligible but get a higher replacement rate when eligible.

For eligible Black claimants, the negative effect of state rules (2.97% in favor of White claimants) is compensated by the positive effect of work history (4.24% in favor of Black claimants) (see col. 5). Overall, this leads to an insignificant racial difference in replacement rates for eligible claimants. However, this lack of a difference is merely accidental: work history differences will not generally compensate inequalities introduced by state rules by design.

The unexplained gap Finally, the fourth line in Table 3 reports the estimates of the unexplained gaps between Black and White claimants (component (iii)). In principle, UI outcomes should only depend on claimants' work history characteristics in each state. In practice, to the extent that they have discretion, UI officers could take into account other characteristics correlated with race, or even race itself. A residual gap would hence be suggestive of discrimination in UI determinations. In all considered outcomes, we find that the Black-White gap completely disappears once we account for differences in work history characteristics and state rules, with a precisely estimated zero for the unexplained gap. Our results suggest that there are no discriminatory practices in the implementation of the rules by UI officers.

6.2 The racial gap in monetary determinations

After analyzing the determinants of the gap in UI generosity overall, we now focus on monetary determinations. Monetary determinations are interesting in their own right as monetary denials represent about half of all denials (see Table 2, col (1)), and monetary determinations are the type of decisions that the literature typically focuses on (Leung and O'Leary (2020), de Souza and Luduvice (2020), Chao (2022)). Moreover, for monetary determinations, we can directly observe all relevant work history variables in 90% of the sample (i.e. the state-months that use the same set of variables for monetary eligibility—see Section 4.2 for more details). The results are presented in Table 4. The first line of col (1)-(2) shows that the gaps in UI arising from monetary determinations are only a bit smaller than the overall gaps: this is not surprising, as Black claimants are disadvantaged in both monetary and non-monetary determinations (Table 2). In monetary determination cases, Black claimants get \$ 76.48 lower weekly benefits (24.9%), and 3.4 ppt lower replacement rate (8.4 %) than White claimants (Black-White gaps in col. 1-2). As expected, the gap in monetary eligibility (col (3)) is smaller than the gap in overall eligibility, but, conditional on being eligible, the gaps in the amount of UI received (col (4) and (5)) are almost identical to the gaps in overall eligibility.

Now, the decomposition of these gaps shows strikingly similar patterns to the decomposition of the gaps in overall UI presented in Table 3. All results discussed in Section 6.1 are qualitatively similar: differences in state rules are always generating a significant negative gap (i.e. to the disadvantage of Black claimants) ; differences in work history generate large negative gaps for all outcomes, except in the replacement rate of eligible claimants ; there is virtually no unexplained gap. Quantitatively, the role of state rules differences appears less important, while work history differences play a larger role. These differences in magnitude probably come from a combination of two factors. First, differences in rules concerning non-monetary determination could be particularly detrimental to Black claimants, and hence amplify the magnitude of the state rule component of the overall UI gap in Table 3. This is consistent with the particularly large negative correlation between the proportion of Black claimant in a state, and the frequency of exceptions to the no-quit rule in Figure 2 (also see Table C.1). Second, measurement error in work history variables lead to under-estimate the size of the work history component, and over-estimate the size of the state rule component in Table 3. The robustness checks discussed in the next section suggests that such biases associated with measurement errors in the work history variables might exist, but appear small. Therefore, the size of the state rule component in Table 4 can be interpreted as a lower bound for the true influence of state rule differences on UI overall. Overall, Table 4 shows that differences in state rules generate substantial gaps between Black and White claimants with similar work history in the outcomes from monetary determinations alone, and the results reinforce the conclusion from our analysis of all determinations.

6.3 Robustness checks

We first test the sensitivity of the results of our analysis of the gap in UI generosity (Table 3) to our use of proxies for work history variables. We re-estimate the various determinants of the racial gap in the outcome of monetary determinations, using either proxies or the actual work history variables in Table D.2. All our qualitative conclusions continue to hold, and the estimates remain quantitatively very close.

Then, we re-estimate the components of the gap in UI generosity, but controlling for additional claimants' characteristics that should not be relevant for UI outcomes (gender, age, education level). If we have omitted important information correlated with race, it might also be correlated with these characteristics, and adding them in our model could then change our estimates for the Black-White gaps. Results are presented in Tables D.3: for all components of the Black-White gaps, our estimates are unaffected by the inclusion of these controls. This provides evidence in favor of our identification assumption that we are not omitting variables that matter for UI and are correlated with race.

Next, we more flexibly estimate the benefit formulas using machine learning. Our main analysis uses linear regression to uncover how work history maps to benefit levels across states. However, UI rules are non-linear, and machine learning models may better capture the non-linearities inherent in all state benefit formulas. For all states, we fit a Random Forests model which predicts the outcomes (weekly benefit amount, approval, and so on) using base period earnings, highest quarter earnings, job separation status, weeks worked, and the ratio of highest quarter earnings to base period earnings. The models are fit using only white claimants as in the main analysis.

In contrast to the linear models, we include year as a predictor because the algorithm can agnostically uncover interactions between year and work history variables as rules change within states. We also use the full sample of new claimants and paid claimants captured later in their spells in order to have a larger sample size for cross-validation. The Random Forest hyper-parameters for each state are selected using a random grid search and 5-fold cross-validation. We uses this fixed set of hyper-parameters when we bootstrap this process to calculate standard errors. In general, the Random Forests predictions fit both White and Black claimants (who are not used to estimate the models) better than the linear regressions.

The results shown in Table D.1 present the same estimates as in Table 3 using the benefit and approval predictions from the Random Forests model. Reassuringly, the estimates align closely with the results in Table 3.

7 Additional results

7.1 Racial bias in the measure of work history variables?

We have assumed so far that the work history variables we control for are "correct". In practice, there might be room for subjective assessment by UI officers, and therefore, there could also be racial differences at this stage of the claim processing. The BAM data offer a direct way to test for racial bias in UI officer's assessment: to the extent that BAM auditors are less racially biased than UI officers, systematic mistakes made by UI officers that disfavor Blacks can be seen as evidence of racial bias. We analyze mistakes detected by BAM auditors in UI outcomes and in three work history variables (the Base period earnings, the Highest quarter earnings, and the determination that claimants separated from their prior job due to lack of work). For each variable, we build a measure of the size of mistakes by taking the original value minus the value determined at the end of the BAM audit: positive mistakes indicate that UI officers' assessments are excessively favorable to claimants. We then analyze the correlation between these mistakes and claimants' characteristics. These correlations cannot be interpreted causally, as claims might have unobserved characteristics that make them deferentially exposed to mistakes. For instance, it could be that Black claimants tend to make claims that have unobserved characteristics that make them more complicated to treat, which could create a correlation between the prevalence of mistakes and race even in the absence of discrimination. In this exercise, we hence merely document observational correlations to assess whether it seems reasonable to ignore the potential racial bias in the assessment of work history variables by UI officers—as we have done in our analysis so far.

We present the results in Table D.4. In col (1), we see that the size of mistakes in the assessment of the weekly benefits amount is not significantly different for Black and White claimants. From col (2), this finding appears to hold when we control for other claimants' characteristics (i.e. gender, age, education, prior occupation and prior industry). Importantly, this finding also holds when we add state fixed effects in col (3): it does not seem that Black workers live in states with systematically more or fewer mistakes in the assessment of weekly benefits. We then examine mistakes in replacement rate: Black claimants appear to receive a 0.7 ppt lower replacement rate due to differential mistakes in replacement rate (col (4)). But this correlation becomes small and insignificant when we control for other claimants' characteristics (col (5) and (6)). Overall, these results suggest that there is no penalty in the UI outcomes received by Black claimants coming from a racial bias in the assessment of work history variables by UI officers.

The rest of Table D.4 examines directly the assessment of some work history variables. The Base period earnings of Black claimants appear to be systemically over-estimated relative to those of White claimants by UI officers (col (7) to (9)), while the Highest quarter earnings appear to be systematically under-estimated ((10) to (12)). Finally, we detect no racial difference in the mistakes concerning the assessment of the reason for separation ((13) to (15)). These additional results hence suggest that there is no bias against black claimants systematically across all the relevant dimensions of work history. Overall, Table D.4 provides no evidence of racial inequality in UI coming from a racial bias in the assessment of work history variables by UI officers. This is consistent with the finding that there is no residual gap in UI (unexplained component (iii) in Tables 3 and 4), after we have accounted for differences in state rules and in work history variables. Thus, the racial inequality in unemployment insurance in not produced by intentional discriminatory behavior by individuals, but built into the design of the institution. In terms of policy, our results suggest that addressing racial inequality in unemployment insurance requires a reform of the institution towards more harmonization of state rules, rather than more monitoring of UI officers behavior.

7.2 Policy simulations

Many arguments have been brought in the public debate in favor of reforming the UI system by enacting minimum federal standards (Bivens et al., 2021) or converting to a fully federal system (Dube, 2021). In particular, the decentralized system might be inefficient, nontransparent, hard to monitor, and makes it difficult to temporarily change replacement rates in case of an emergency (as visible with the Cares Act in 2020). In this section, we focus on how racial inequality can be decreased by partially harmonizing the UI system across states and increasing the overall generosity in various dimensions. Indirectly, this analysis helps highlight which dimension of the current system contributes the most to the existing racial inequality. Our microdata on claims are uniquely well-suited to simulate the effect on UI received of various reforms of the UI system. The racial gap generated by state rules differences would mechanically disappear if all states had the same UI rules, as visible from formula (3). But how would the racial gap change if only one aspect of state rules was harmonized? We successively consider four partial reforms consisting in the harmonization of four different rule parameters across states: (1) the cap on weekly benefits, (2) the minimum weekly benefits, (3) the amount of base periods earnings required for eligibility, and (4) the eligibility rate of people who quit their jobs (as workers who quit their job with a good cause can be eligible for UI in some states and not in others).[16]

[16]We don't observe the reasons for quits in the data, but we assume that their composition is similar in all states. We can hence assume that the eligibility rate of job quitters is only determined by the strictness of the state.

The first two rule parameters considered concern the way WBA is computed for those who are eligible, while the last two rule parameters concern the eligibility criteria. We simulate harmonization scenarios where we vary the minimum level of generosity that is decided at the federal level: this minimum will be binding for all states that currently have a lower level of generosity, while other states will not be affected (i.e. no state will decrease its generosity). We successively set the federal minimum at various quartiles of the distribution of the rule parameter in our study period and at the maximum (then, all states have the same parameter). We consider the direct effect of these policy changes on the racial gap in replacement rate, assuming that the composition of claimants remains unchanged.[17]

We present the results in Figure 3: in each panel, the red horizontal line stands for the current Black-White gap in UI explained by state rules, while the faint red horizontal line represents the current total Black-White gap in UI. Therefore, a policy reform that pushes the dark blue bar above the red line lowers the gap explained by state rules, and a policy reform that pushes the light blue bar above the faint red line lowers the overall Black-White gap. Let's first consider the reforms of the computation of benefits. In Panel (1), we see that harmonizing the maximum WBA alone would already substantially decrease the gap in replacement rate explained by state rules: the 8.4% actual gap due to state rules would be reduced to 7% if the federal cap was set at the median of the cap distribution, and to 6.5% if the cap was set at the maximum of the cap distribution. This should not be surprising, given that the cap on WBA is one of the aspects of state rule generosity that is the most (inversely) correlated with the share of Black claimants (See Figure 2, and Table C.1)). While the gap explained by state rules would decline with WBA harmonization, the total Black-White gap would actually increase from 18.3% (Table 3, col. 2, bottom panel Gap/White mean) to above 20%. This is because White claimants tend to have higher prior earnings, and hence benefit more from a higher cap on WBA. Conversely, we see in Panel (2) that harmonizing the minimum level of WBA that eligible claimants receive has a limited effect on the gap explained by state rules, but greatly decreases the overall gap.

Let's now consider the reforms of the eligibility criteria. In Figure 3 Panel (3), we simulate the effect of a harmonization of the earnings requirement (the higher they are, the less generous the state is). Setting a maximum required Base Period Earnings at the third quartile of the distribution (i.e. requiring $2964 of earnings during the base period) would already decrease the gap induced by state rules differences from 8.4% (Table 3, col. 2, bottom panel (i)/White mean) to 7.2%, while also reducing the overall gap in replacement rate to 13%. For comparison, the reform suggested by Dube (2021) would set the earnings requirement to $1500 during the base period, which lies between the median and the third quartile.[18] In Panel (4), we harmonize the requirements for separation eligibility. When we

[17] We discuss evidence suggesting it might be a reasonable assumption in Section 8.2.

[18] More specifically, Dube (2021) recommends setting the requirement to$1000 during the highest quarter,

align the treatment of quitters to the most generous state, the gap explained by state rules differences is reduced to 6.2%, and the overall gap is reduced to 14.4%.

Overall, the key take-away from this simulation exercise is that harmonizing eligibility requirements is the best way to reduce racial inequality in the UI system (i.e. the gap explained by state rules differences), while also decreasing the overall racial gap. Intuitively, this is because these measures both decrease the racial gap and increase UI generosity towards claimants with the lowest earnings. This is illustrated in Figure D.1: we present the average replacement rate for claimants in different quintiles of the distribution of prior hourly wages, under each policy reform. The UI system gives the highest replacement rate in the middle of the prior-wages distribution: claimants with the highest prior earnings receive a lower replacement rate as the maximum WBA is more likely to be binding for them (Panel (1)), while claimants with the lowest prior earnings receive lower replacement rates as they are less likely to be eligible (Panels (3) and (4)). As Black claimants tend to have lower earnings, any UI reform that increases the generosity of the UI system for low-earnings workers will decrease the racial gap explained by racial differences in work history.

Additionally, we present in Figure D.2 a measure of the overall cost corresponding to each policy reform we considered: the average weekly benefits amount per claimant (whether eligible or not). Under the assumption that claiming behavior does not change across policy reforms, the number of claimants stays the same, so the WBA per claimant is proportional to the total benefits paid under each policy reform. Fully harmonizing the cap on WBA (i.e. setting it to the current maximum across states) is the most expensive policy: the average WBA per claimant reaches $294, which is 19% more than the actual average of $248. In contrast, harmonizing the minimum WBA only increases the average WBA to at most $259 (a 4% increase). The two reforms harmonizing eligibility criteria increase the cost to at most $263 (panel 3) and $265 (panel 4), i.e. by 6 or 7%. Harmonizing eligibility requirements hence also appears to be the most cost effective single measure.

Overall, our analysis shows that, in case a partial federalization reform is considered, imposing a federal maximum for eligibility requirements could be the best way to decrease racial inequality, and make the UI system more progressive overall. Such a policy is also supported by recent findings of the positive welfare impact of a decrease in eligibility requirement in Leung and O'Leary (2020).

7.3 Heterogeneity in the racial UI gaps

What is driving the heterogeneity in the racial gap in UI? In Figure D.3 (upper part), we present the Black-White gap in replacement rate, eligibility rate, and replacement rate conditional on eligibility for claimants in different quintiles of the prior wage distribution.[19]

and $500 in a second quarter during the base period

[19]We implement the same analysis for other heterogeneity dimensions in Figure D.4 and Figure D.5.

Interestingly, we see from Panel (A.1) that, although the racial gap is much larger for claimants with lower prior wage, the gap explained by state rule differences is lower for these groups. Why is that? The gap in the replacement rate of eligible workers that is explained by state rules is larger for those with higher prior wages (Panel (A.3)). In contrast, the gap in eligibility explained by state rules differences appears flatter across prior wage groups (Panel (A.2)). In the lower part of Figure D.3, we examine the effect of various policy reforms on the racial gap across prior wage groups. Consistent with prior results, harmonizing the cap on WBA decreases the racial gap explained by state rule differences, but only for the two highest quintiles. Harmonizing the minimum WBA level has very limited effects. In contrast, harmonizing eligibility requirements reduces the racial gap primarily at the bottom of the prior wage distribution.

8 Discussion

8.1 Other gaps?

We have emphasized the racial gaps in UI arising from differences in rules across states. But such differences could a priori generate gaps between any group that is unequally spread on the US territory. Do state rules differences generate gaps across other demographic groups? In Figure 4, we present graphically the different components of the gaps in weekly benefits amount and in replacement rate between Black and White claimants, between women and men, between claimants below and above 40 years old, and between claimants from with more or less than some college education. We present both the overall gap (full bar), and the gap explained by state rules differences (dark blue part of bar). Overall, women and younger claimants also tend to receive a lower replacement rate than men and older claimants, respectively, though these gender and age gaps are about half the size of the racial gap. But interestingly, there is virtually no gender gap nor age gap explained by differences in state rules. Therefore, gaps in both overall UI replacement rate and in the portion explained by state rules are the largest in the racial dimension as opposed to other demographics we examine. These results support our focus on the consequences of the UI system for racial inequality.

Although this is beyond the scope of our paper to test this causal link, we note that the results in 4 are consistent with the idea that the negative correlation between state rules generosity and the Black population is not a coincidence, but instead that Southern states may have persistently had stricter rules *because of* their large Black population. Katznelson (2006) argue that, when the UI was enacted in the U.S. in 1935, Democrats from Southern states imposed a decentralized system and chose a minimal level of generosity to avoid redistributing income towards their Black residents.

8.2 Racial gaps and state rules among all unemployed workers

We have documented the racial gap in UI received by UI claimants, focusing on the share of the raw gap that is explained by state rule differences. As we documented, not all unemployed workers claim UI. Here, we extend our analysis to all unemployed workers. What would happen if all unemployed workers did claim UI or if UI filing were automatic? How much of the gap in UI receipt would be explained by state rules? To answer this question, we analyze the gap in potential UI among all unemployed workers, assuming they all claimed. The potential gap in UI explained by state rules differences among all unemployed workers is an important measure, as one might consider that a fair situation is one where Black and White claimants with the same work history could receive the same benefits *if* they claimed. From expression (4), one can see that the racial gap explained by state differences among claimants could differ from that among unemployed for two reasons (we use the same notations as in Section 4.1 and the superscript u to denote the population of unemployed workers)[20]:

- $\sum_k \left((\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot (\overline{X_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) \right) \neq \sum_k \left((\overline{S^u_{b,k}} - \overline{S^u_{w,k}}) \cdot (\overline{X^u_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) \right)$ i.e. if the correlations between state rules generosity and the representation gap (i.e. gap in the share of each racial group living in the state) are different in the population of unemployed workers and in the population of claimants.
- $\sum_k \left((\overline{X_{b,k}} - \overline{X_{w,k}}) \cdot \overline{S_{w,k}} \cdot \widetilde{\alpha}_{1,k} \right) \neq \sum_k \left((\overline{X^u_{b,k}} - \overline{X^u_{w,k}}) \cdot \overline{S^u_{w,k}} \cdot \widetilde{\alpha}_{1,k} \right)$ i.e. if the correlations between the state-specific premium on work history and the work history gap in the state are different in the population of unemployed workers and in the population of claimants.

Whether these correlations are the same in the population of claimants and in the population of the unemployed are empirical questions. Though in theory, unemployed workers can be expected to claim more if they can gain better UI outcome from it, many other factors can influence claiming patterns in practice. For instance, Black and White unemployed workers might be differently informed about UI rules, expect to have different unemployment spells, have different levels of savings, etc. To test whether the correlations are different, we measure them in the population of unemployed workers using the CPS, and compare them to the correlations we observe in the population of claimants, using our study dataset. In Figure D.6, Panel (1) presents the correlation of state generosity with the state racial representation gaps among claimants (in red), and among unemployed workers (in blue); this speaks to the first component in the itemized list above. We see that in both cases, state rule generosity is negatively correlated with the representation of the black population in the state, and that the correlations are not statistically significantly different in the two populations. In other terms, Black claimants are less likely to live in

[20]See more details in Appendix E.1.

generous UI states, and that is similarly true for Black unemployed people overall. Panel (2) presents the correlation of state generosity with the state racial gaps in prior wages among claimants (in red), and among unemployed workers (in blue); this speaks to the second component in the itemized list above. This Figure shows that there is no significant correlation between state UI generosity and the Black-White gap in prior wages, and this is true both among claimants and among all unemployed.

In sum, we find no evidence of differential selection patterns into claiming across race that would be correlated with state generosity. To complement these results, we also analyze the density of claims around the eligibility threshold in Appendix E.2: we find that state UI rules do not affect the propensity to claim around the eligibility threshold consistent with O'Leary, Spriggs, and Wandner (2021).[21] This results hold for Black and White workers, we we analyze the density of claims separately of each race group. These analyses overall indicate that our estimate of the impact of state rule differences on the racial gap in UI among claimants should provide a good measure of the impact of state rule differences on the racial gap in UI among all unemployed workers.

8.3 Location choice

We have documented a racial gap in the replacement rate of unemployment insurance, and we have shown that this gap could be substantially reduced by harmonizing rules across states. But, how important is it, from a welfare perspective, to reduce this gap? This may not be so important if the gap reflects compensating differentials across states: states with worse UI benefits might be otherwise better for Black workers. This compensating differential pattern would arise as Black workers sort across states to maximize their utility. However, workers' geographic mobility is limited, with similar degrees of mobility for Blacks and Whites (Molloy, Smith, and Wozniak, 2017). US internal migration has been declining since 1980 (Molloy, Smith, and Wozniak, 2017), and the migration response of workers to changes in local economic conditions is limited (Dao, Furceri, and Loungani, 2017; Yagan, 2019), especially for lower skill workers (Wozniak, 2010). This is consistent with relatively high moving costs. Because of these high moving costs equal to at least one yearly income (Kosar, Ransom, and van der Klaauw, 2021), workers cannot be expected to move just to optimize unemployment insurance benefits. Consistent with high moving costs, the geographic distribution of the Black population across US states has remained similar since 1860 (appendix Figure C.4). The distribution of the Black population across US states in 2020 is very close to the distribution in 1930, i.e. prior to the creation of the unemployment insurance system. Given the body of existing evidence, we conclude that differences in replacement rates across states are unlikely to be fully offset by compensating

[21] These results are also in line with the finding from Johnston and Mas (2017) and Schmieder, von Wachter, and Bender (2016) that there is no sharp changes in claiming in response to dramatic changes in benefit rules.

state amenities, and that harmonizing benefits across states is likely more feasible than moving Black workers across states.

9 Conclusion

The unemployment insurance (UI) system offers a unique opportunity to measure three key factors behind racial economic inequality: institutional factors, pre-existing inequality (here, in work history), and individual discriminatory behavior. We first document a raw 18.28% Black-White gap in the UI received by claimants. Then, using a Oaxaca-Blinder style decomposition, we show that, after taking into account work history, essentially all of the Black-White gap in replacement rate can be explained by differences in state UI rules. We find no evidence for residual discrimination in the application of UI rules. Ensuring that Black and White claimants with the same work history receive the same insurance against job loss would hence require harmonizing UI rules across states. We also examine partial reforms, and we show that setting a national maximum for the monetary eligibility requirement would be particularly useful to narrow down the racial gap, while at the same time providing more insurance against job loss for low-wage workers of any race.

Our findings highlight an important type of racial inequality: lower access to UI implies that Black workers losing their job likely suffer relatively large welfare costs during unemployment—especially since they hold lower levels of liquid assets to self-insure(Ganong et al., 2021), and face increased difficulties finding a new job due to racial discrimination in hiring (Kline, Rose, and Walters, 2021). Receiving lower unemployment insurance might also induce them to accept lower-paying jobs, which could further lower their income after unemployment (Nekoei and Weber, 2017).

Most importantly, our paper highlights that the design of the UI rules plays a key role in generating this inequality, rather than discrimination in the implementation of the rules. Therefore, racial economic inequality can persist even in the absence of individual discriminating behavior. The UI system is not an isolated case: differences in state-level rules may also generate racial gaps in the receipt of the main welfare cash transfer program for poor families, the Temporary Assistance for Needy Families (Parolin (2021)) ; differences in the allocation of public spending decided at the city, metropolitan area or county level may generate racial gaps in the quality of public services, like education (Alesina, Baqir, and Easterly (1999)). Beyond local differences, other aspects of the design of ostensibly race-neutral policies can generate large racial disparities that are not justified by the policies' ultimate goals (as demonstrated by Rose (2021) for the justice system). Research findings that people tend to dislike re-distributive policies when they disproportionately benefit other racial groups (eg Alesina, Glaeser, and Sacerdote (2001)) suggest that policy designs that disadvantage racial minorities might be common. Highlighting the racial gaps generated by ostensibly race-neutral policies is hence key to understanding and addressing racial inequality in the U.S. and in other contexts with racial diversity.

Bibliography

Aaronson, Daniel, Daniel Hartley, and Bhashkar Mazumder. 2021. “The Effects of the 1930s HOLC âRedliningâ Maps.” *American Economic Journal: Economic Policy* 13 (4):355–392. URL https://pubs.aeaweb.org/doi/10.1257/pol.20190414.

Alesina, Alberto, Reza Baqir, and William Easterly. 1999. “Public Goods and Ethnic Divisions.” *The Quarterly Journal of Economics* 114 (4):1243–1284.

Alesina, Alberto, Matteo F. Ferroni, and Stefanie Stantcheva. 2021. “Perceptions of Racial Gaps, Their Causes, and Ways to Reduce Them.” Tech. Rep. w29245, National Bureau of Economic Research.

Alesina, Alberto, Edward Glaeser, and Bruce Sacerdote. 2001. “Why Doesn’t the US Have a European-Style Welfare System?” Tech. Rep. w8524, National Bureau of Economic Research.

Anderson, P. M. and B. D. Meyer. 1997. “Unemployment Insurance Takeup Rates and the After-Tax Value of Benefits.” *The Quarterly Journal of Economics* 112 (3):913–937. URL https://academic.oup.com/qje/article-lookup/doi/10.1162/003355397555389.

Auray, Stéphane, David L. Fuller, and Damba Lkhagvasuren. 2019. “Unemployment insurance take-up rates in an equilibrium search model.” *European Economic Review* 112:1–31. URL https://www.sciencedirect.com/science/article/abs/pii/S0014292118301855. Publisher: North-Holland.

Baicker, Katherine, Claudia Goldin, and Lawrence F Katz. 2007. *7. A Distinctive System: Origins and Impact of US Unemployment Compensation*. University of Chicago Press.

Bivens, Josh et al. 2021. “Reforming Unemployment Insurance: Stabilizing a System in Crisis and Laying the Foundation for Equity.” *Economic Policy Institute, National Employment Law Project, Center for American Progress, Center for Popular Democracy, Groundwork Collaborative, National Womenâs Law Center and Washington Center for Equitable Growth* :50.

Blank, Rebecca M. and David E. Card. 1991. “Recent Trends in Insured and Uninsured Unemployment: Is There an Explanation?*.” *The Quarterly Journal of Economics* 106 (4):1157–1189. URL https://doi.org/10.2307/2937960.

Blasco, Sylvie and François Fontaine. 2021. “Unemployment Duration and the Take-Up of Unemployment Insurance.”

Chao, Ying. 2022. “A Quantitative Analysis of Relaxing UI Eligibility Requirements: Evidence from the Pandemic Unemployment Assistance.”

Dao, Mai, Davide Furceri, and Prakash Loungani. 2017. "Regional Labor Market Adjustment in the United States: Trend and Cycle." *The Review of Economics and Statistics* 99 (2):243–257. URL `https://doi.org/10.1162/REST_a_00642`.

de Souza, Gustavo and André Victor Luduvice. 2020. "Optimal Unemployment Insurance Requirements."

Derenoncourt, Ellora and Claire Montialoux. 2021. "Minimum Wages and Racial Inequality*." *The Quarterly Journal of Economics* 136 (1):169–228.

Dube, Arindrajit. 2021. "A Plan to Reform the Unemployment Insurance System in the United States — The Hamilton Project." https://www.hamiltonproject.org/papers/a_plan_to_reform_the_unemployment_insurance_system_in_t

Ebenstein, Avraham and Kevin Stange. 2010. "Does inconvenience explain low take-up? Evidence from unemployment insurance." *Journal of Policy Analysis and Management* 29 (1):111–136. URL `https://onlinelibrary.wiley.com/doi/10.1002/pam.20481`.

Feigenberg, Benjamin and Conrad Miller. 2021. "Racial divisions and criminal justice: Evidence from southern state courts." *American Economic Journal: Economic Policy* 13 (2):207–40.

Ferraro, Domenico, Nir Jaimovich, Francesca Molinari, and Cristobal Young. 2020. "The Safety Net as a Springboard? A General Equilibrium based Policy Evaluation." *CEPR Discussion Papers* (14786).

Fontaine, François and Andreas Kettemann. 2019. "Quasi-experimental Evidence on Take-up and the Value of Unemployment Insurance,."

Fortin, Nicole, Thomas Lemieux, and Sergio Firpo. 2011. "Chapter 1 - Decomposition Methods in Economics." In *Handbook of Labor Economics*, vol. 4, edited by Orley Ashenfelter and David Card. Elsevier, 1–102. URL `https://www.sciencedirect.com/science/article/pii/S0169721811004072`.

Ganong, Peter, Damon Jones, Pascal Noel, Diana Farrell, Fiona Greig, and Chris Wheat. 2021. "Wealth, Race, and Consumption Smoothing of Typical Income Shocks." .

Gibson, Campbell and Jay Jung. 2002. "Historical Census Statistics on Population Totals By Race, 1790 to 1990, and By Hispanic Origin, 1970 to 1990, For The United States, Regions, Divisions, and States." *Population Division US Census Bureau* Working Paper Series No. 56. `https://web.archive.org/web/20080725044857/http://www.census.gov/population/www/documentation/twps0056/twps0056.html`.

Gilens, Martin. 2000. *Why Americans Hate Welfare: Race, Media, and the Politics of Antipoverty Policy.* Studies in Communication, Media, and Public Opinion. Chicago, IL: University of Chicago Press.

Gould-Werth, Alix and H. Luke Shaefer. 2012. "Unemployment Insurance participation by education and by race and ethnicity." *Monthly Lab. Rev.* 135:28.

Grant-Thomas, Andrew. 2011. "Why Are African Americans and Latinos Underrepresented Among Recipients of Unemployment Insurance and What Should We Do About It?" *Poverty & Race* 8.

Johnston, A. and A. Mas. 2017. "Potential Unemployment Insurance Duration and Labor Supply: The Individual and Market-Level Response to a Benefit Cut." *Jounal of Political Economy* .

Katznelson, Ira. 2006. *When Affirmative Action Was White- An Untold History of Racial Inequality in Twentieth-Century America.* W. w. norton ed.

Kline, Patrick M., Evan K. Rose, and Christopher R. Walters. 2021. "Systemic Discrimination Among Large U.S. Employers." Working Paper 29053, National Bureau of Economic Research. URL `https://www.nber.org/papers/w29053`. Series: Working Paper Series.

Kosar, Gizem, Tyler Ransom, and Wilbert van der Klaauw. 2021. "Understanding migration aversion using elicited counterfactual choice probabilities." *Journal of Econometrics* URL `https://www.sciencedirect.com/science/article/pii/S0304407621000415`.

Kuka, Elira and Bryan A. Stuart. 2021. "Racial Inequality in Unemployment Insurance Receipt and Take-Up." .

Lachowska, Marta, Isaac Sorkin, and Stephen A Woodbury. 2021. "Firms and Unemployment Insurance Take-Up." :74.

Latimer, Melissa. 2003. "A comprehensive analysis of sex and race inequities in unemployment insurance benefits." *J. Soc. & Soc. Welfare* 30:95.

Leung, Pauline and Christopher O'Leary. 2020. "Unemployment Insurance and Means-Tested Program Interactions: Evidence from Administrative Data." *American Economic Journal: Economic Policy* 12 (2):159–192.

Lieberman, Robert C. 2001a. *Shifting the Color Line: Race and the American Welfare State.* Harvard University Press.

———. 2001b. *Shifting the Color Line: Race and the American Welfare State.* Harvard University Press.

Lovell, Vicky. 2002. "Constructing social citizenship: The exclusion of African American women from unemployment insurance in the US." *Feminist Economics* 8 (2):191–197.

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak. 2017. "Job Changing and the Decline in Long-Distance Migration in the United States." *Demography* 54 (2):631–653. URL `https://www.jstor.org/stable/45047263`. Publisher: [Population Association of America, Springer].

Nekoei, Arash and Andrea Weber. 2017. "Does Extending Unemployment Benefits Improve Job Quality?" *American Economic Review* 107 (2):527–561.

Nichols, Austin and Margaret Simms. 2012. "Racial and Ethnic Differences in Receipt of Unemployment Insurance Benefits During the Great Recession." URL `https://www.urban.org/research/publication/racial-and-ethnic-differences-receipt-unemployment-insurance-benefits-during-great-`

O'Leary, Christopher, William Spriggs, and Stephen Wandner. 2022. "Equity in Unemployment Insurance Benefit Access." *AEA Papers and Proceedings* 112.

O'Leary, Christopher J, William E Spriggs, and Stephen A Wandner. 2021. "Equity in Unemployment Insurance Benefit Access." .

Parolin, Zachary. 2021. "Temporary Assistance for Needy Families and the Black–White Child Poverty Gap in the United States." *Socio-Economic Review* 19 (3):1005–1035.

Reticker, Ruth. 1942. "Variations in Benefit Rights Under State Unemployment Compensation Laws." *Soc. Sec. Bull.* 5:4. `https://www.ssa.gov/policy/docs/ssb/v5n6/v5n6p4.pdf`.

Rose, Evan K. 2021. "Who Gets a Second Chance? Effectiveness and Equity in Supervision of Criminal Offenders." *The Quarterly Journal of Economics* 136 (2).

Schmieder, Johannes F., Till von Wachter, and Stefan Bender. 2016. "The Effect of Unemployment Benefits and Nonemployment Durations on Wages." *American Economic Review* 106 (3):739–777.

Schmieder, Johannes F. and Till von Watcher. 2016. "The Effects of Unemployment Insurance Benefits: New Evidence and Interpretation." *The Annual Review of Economics* .

Shaefer, H. Luke. 2010. "Identifying Key Barriers to Unemployment Insurance for Disadvantaged Workers in the United States." *Journal of Social Policy* 39:439–460. URL `https://www.proquest.com/docview/347101947/abstract/A03ADB2C111845A9PQ/1`.

Small, Mario L. and Devah Pager. 2020. "Sociological Perspectives on Racial Discrimination." *Journal of Economic Perspectives* 34 (2):49–67. URL `https://www.aeaweb.org/articles?id=10.1257/jep.34.2.49`.

USDOL. 2019. "Department of Labor Handbook on UI eligibility." `https://oui.doleta.gov/unemploy/pdf/uilawcompar/2019/monetary.pdf`.

Woodbury, Stephen A. 2002. "Unemployment insurance overpayments and underpayments." .

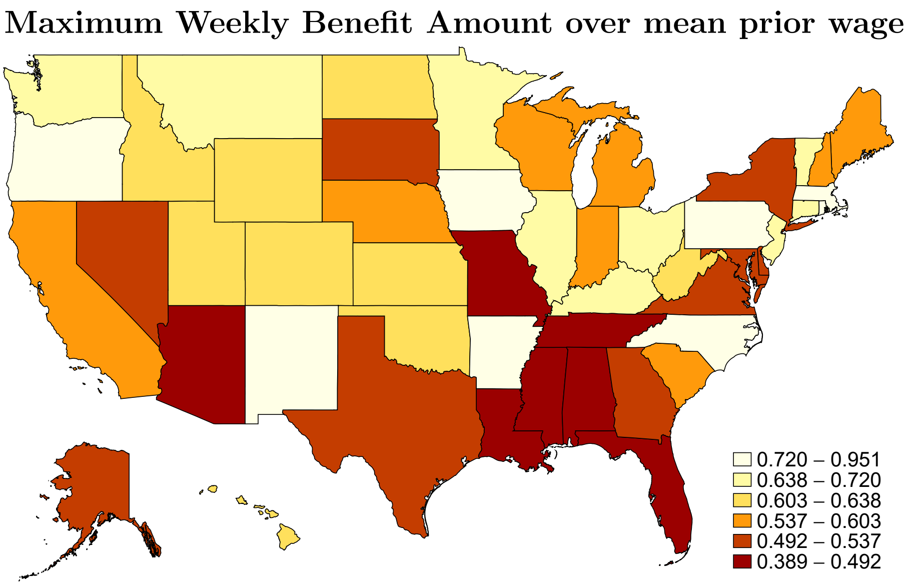
Woodbury, Stephen A and Wayne Vroman. 2000. "Denied Claims Accuracy Pilot Project: Follow-Up Report." .

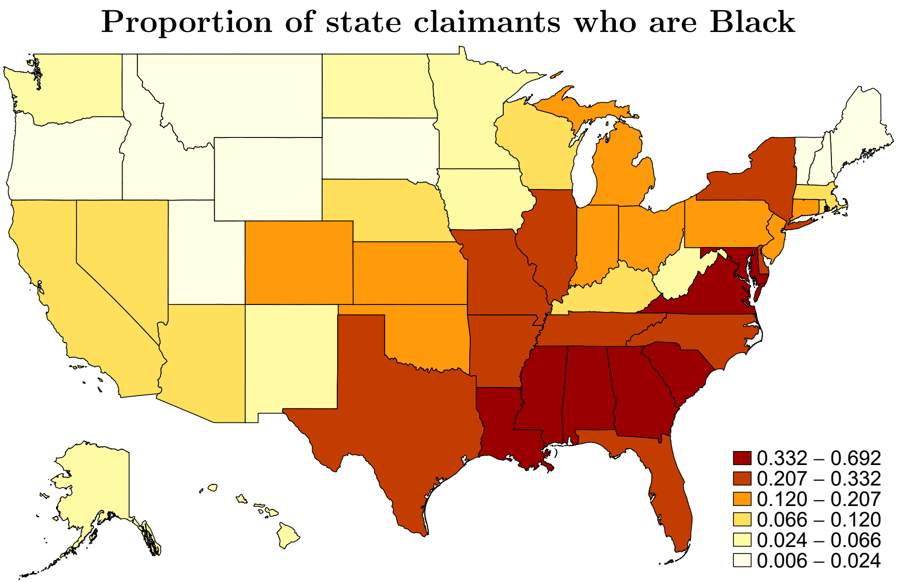
Wozniak, Abigail. 2010. "Are College Graduates More Responsive to Distant Labor Market Opportunities?" *Journal of Human Resources* 45 (4):944–970. URL `http://jhr.uwpress.org/content/45/4/944`.

Yagan, Danny. 2019. "Employment Hysteresis from the Great Recession." *Journal of Political Economy* 127 (5):2505–2558. URL `https://www.journals.uchicago.edu/doi/full/10.1086/701809`. Publisher: The University of Chicago Press.

10 Tables and Figures

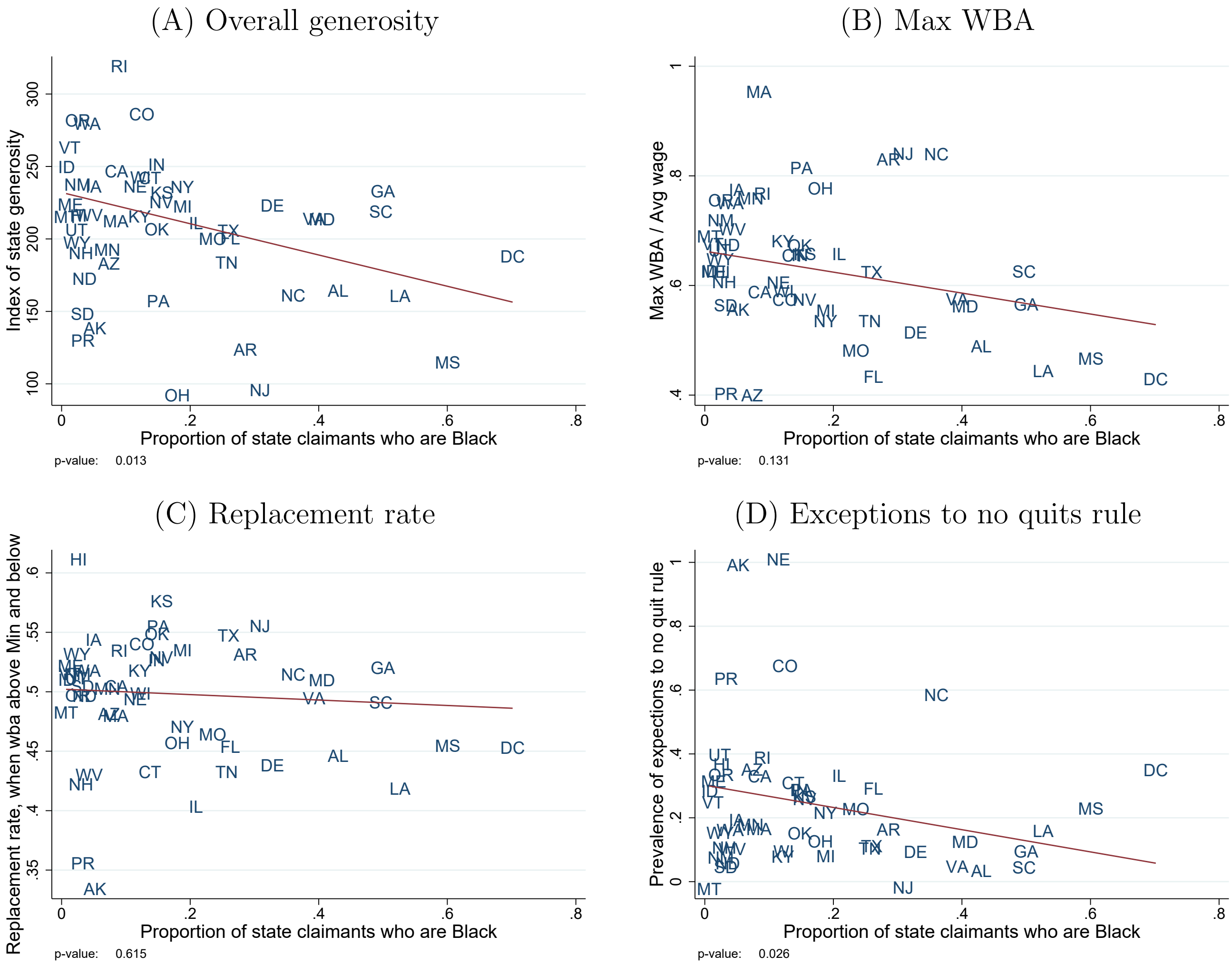
Figure 1: Maximum Weekly Benefit Amount and share of Black claimants





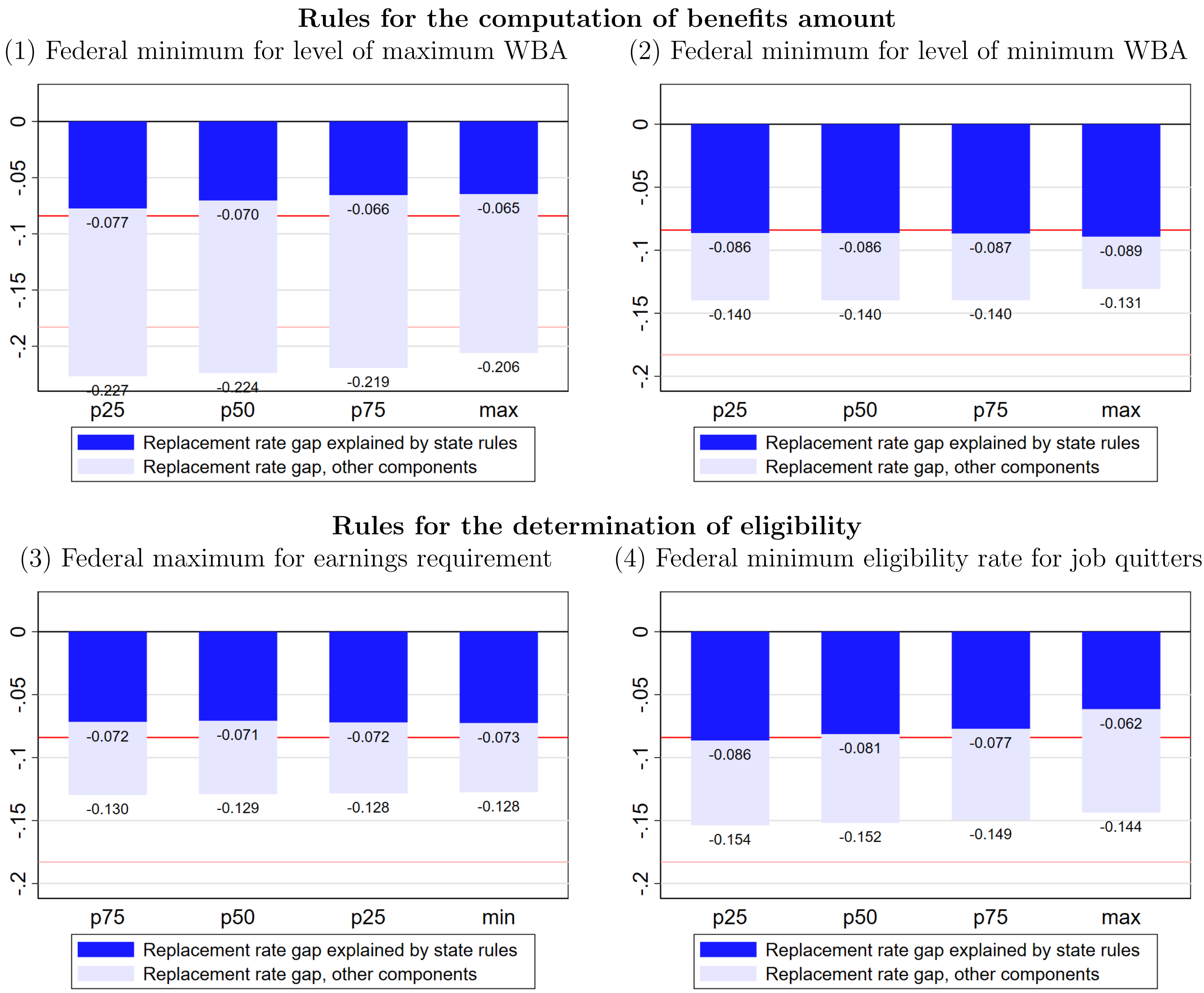
Notes: These two maps illustrate the negative correlation between state generosity in their UI rules, and their proportion of Black UI claimants. The first map represents the level of the statutory cap on the weekly benefits amount according to the rule in each US state, over the average weekly wage of claimants in the state. This provides one measure of UI generosity in the state (we analyze other measures in Figure 2). The darker the color, the lower the benefits amount claimants can receive. The second map represents the share of Black claimants in the state. The darker the color, the higher fraction of Black claimants in the state.

Figure 2: State rules and racial composition



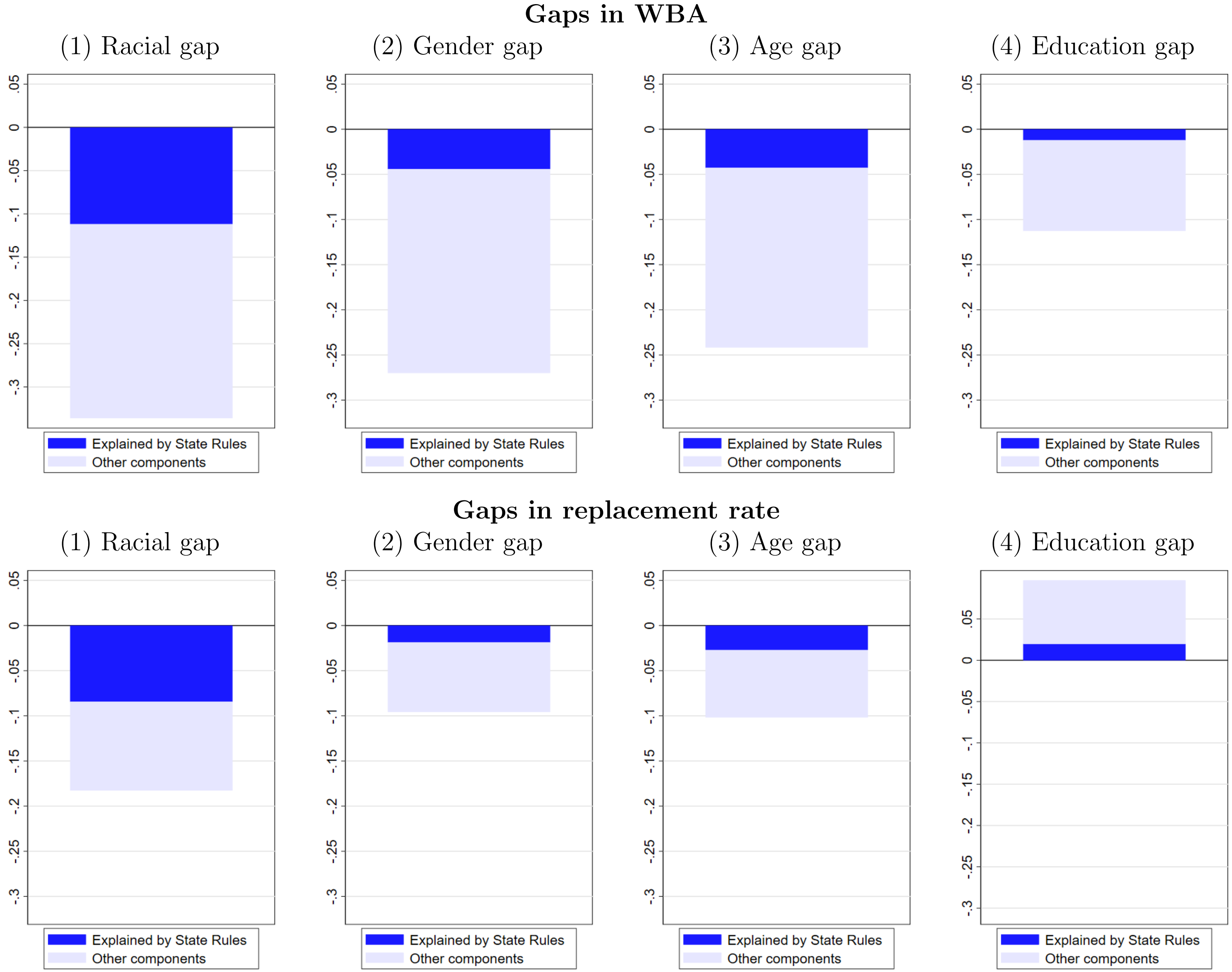
Note: This Figure presents the correlation of state rule generosity and the share of claimants in the state who is Black. We measure state generosity using an index summarize all dimensions of state rules in Panel (A) (see Section 5.3) ; the statutory maximum level of weekly benefits in Panel (B) ; the multiplicative term used to compute weekly benefits (WBA over weekly BPE) for claimants who receive a WBA above the minimum and below the maximum in Panel (C) ; the proportion of claimants quitting their jobs who are eligible in Panel (D). All earnings variable are normalized by the average prior wage earned by claimants in the state, to account for differences in price levels across states. We present the regression line and the corresponding p-value, obtained when each state is weighted by its number of claimants.

Figure 3: Policy simulation



Notes: We present the racial gap under various hypothetical policy reforms: if we harmonize the cap on WBA (in (1)), the minimum level of WBA (in (2)), the minimum BPE required for eligibility (in (3)), and the rate of eligibility for job quitters (in (4)). Each bar represents the gap in replacement rate under a specific scenario in relative term (%), and the part in dark blue represents the gap explained by state rules differences. The red horizontal lines denote the actual gaps in replacement rate: overall (light red, 18.3% of the White mean), explained by state rule differences (dark red, 8.4% of the White mean). For each policy parameter, we assume that there is a federal minimum level generosity fixed to a specific quartile of the distribution of the parameter in our study sample: for the cap on WBA, p25 corresponds to \$418, p50: \$485, p75: \$567 and max: \$1122 ; for the min WBA, p25: \$50, p50: \$66 , p75: \$81, max: \$228 ; for Base Period Earnings requirement, p75 corresponds to \$2964, p50: \$2091, p25: \$1125 and the minimum to \$130 ; for the rate of eligibility for job quitters, p25: 0, p50: 0, p75: 0.33 and max: 1. All prices are CPI adjusted (in 2019 \$).

Figure 4: Gaps in UI between various groups



Note: This Figure represents the racial gap (Black relative to White), the gender gap (women relative to men), the age gap (workers below 40 years old relative to those above), and the education gap (workers without any college education relative to more educated workers). We present the gap in weekly benefits amount (upper panel) and in replacement rate (lower panel) in relative term (in ppt). The full bar represents the total gap, and the bar in dark blue represents the gap explained by state rules differences.

Table 1: Description of new UI recipients, new UI applicants, and unemployed workers

Variable	(1) Claimants (BAM)	(2) Eligible claimants (BAM)	(3) Unemployed (CPS)
Race			
White	0.695	0.731	0.741
	(0.460)	(0.443)	(0.438)
Black	0.195	0.166	0.187
	(0.396)	(0.372)	(0.390)
Asian	0.025	0.025	0.036
	(0.156)	(0.157)	(0.186)
American Indian / Alaskan Native	0.013	0.012	0.014
	(0.115)	(0.111)	(0.116)
Native Hawaiian / Oth. Pacific Islander	0.005	0.004	0.003
	(0.068)	(0.065)	(0.059)
Multiple races	0.011	0.010	0.019
	(0.105)	(0.100)	(0.138)
Race Unknown	0.056	0.050	0.000
	(0.230)	(0.219)	(0.000)
Ethnicity			
Hispanic	0.165	0.160	0.183
	(0.372)	(0.366)	(0.387)
Non-Hispanic	0.796	0.804	0.816
	(0.403)	(0.397)	(0.388)
Unknown	0.038	0.036	0.001
	(0.191)	(0.187)	(0.030)
Gender			
Male	0.575	0.600	0.601
	(0.494)	(0.490)	(0.490)
Female	0.425	0.400	0.399
	(0.494)	(0.490)	(0.490)
Age			
<25	0.120	0.094	0.170
	(0.325)	(0.291)	(0.375)
25-34	0.260	0.244	0.243
	(0.438)	(0.429)	(0.429)
35-44	0.237	0.245	0.214
	(0.425)	(0.430)	(0.410)
45-54	0.227	0.246	0.210
	(0.419)	(0.430)	(0.407)
55+	0.157	0.172	0.163
	(0.364)	(0.378)	(0.369)
Education			
Less than high school	0.143	0.142	0.155
	(0.350)	(0.349)	(0.362)
High school	0.424	0.418	0.395
	(0.494)	(0.493)	(0.489)
Some college	0.289	0.283	0.270
	(0.453)	(0.450)	(0.444)
Bachelors or more	0.133	0.141	0.180
	(0.340)	(0.348)	(0.384)
Observations	194,481	23,250	497,478

Notes: We present proportion of different demographic groups in the population of new UI claimants and new eligible UI claimants using our BAM study sample (col (1) and (2)), and in the population of unemployed workers using the CPS for 2002-2017, excluding re-entrants and new entrants (col (3)). Standard deviations are reported in parentheses.

Table 2: Description of UI outcomes for claimants, by race

Variable	(1) All	(2) Black	(3) White	(4) Other
UI Outcomes				
Weekly benefit amount	234.83	170.23	256.50	212.08
	(186.07)	(165.43)	(186.62)	(187.87)
Weekly benefit amount, if eligible	327.10	277.53	339.55	318.50
	(134.34)	(121.82)	(133.80)	(138.27)
Replacement rate	0.34	0.29	0.36	0.32
	(0.26)	(0.27)	(0.26)	(0.28)
Replacement rate, if eligible	0.47	0.47	0.47	0.49
	(0.18)	(0.17)	(0.18)	(0.19)
Eligible for UI	0.72	0.61	0.76	0.67
	(0.45)	(0.49)	(0.43)	(0.47)
Denied for monetary reason	0.13	0.18	0.11	0.14
	(0.33)	(0.38)	(0.31)	(0.35)
Denied for separation reason	0.11	0.16	0.10	0.13
	(0.31)	(0.36)	(0.29)	(0.34)
Denied for other reason	0.04	0.05	0.04	0.06
	(0.20)	(0.22)	(0.19)	(0.25)
UI-relevant work history				
Highest quarter earnings (in thousands)	29.54	20.85	32.28	26.06
	(29.38)	(20.14)	(31.18)	(26.90)
Base period earnings (in thousands)	10.09	7.30	10.96	9.14
	(9.05)	(6.11)	(9.68)	(7.81)
Weeks worked	34.43	29.12	36.40	24.49
	(18.14)	(19.34)	(17.08)	(21.21)
Separation: Lack of work	0.61	0.46	0.64	0.61
	(0.49)	(0.50)	(0.48)	(0.49)
Separation: Voluntary quit	0.09	0.12	0.09	0.12
	(0.29)	(0.32)	(0.28)	(0.33)
Separation: Discharge	0.23	0.33	0.20	0.20
	(0.42)	(0.47)	(0.40)	(0.40)
Observations	194,545	44,100	124,822	25,623

Notes: Table reports the mean UI outcomes and work history variables for new claimants, using our BAM study sample. All incomes are in 2019 dollars using the CPI downloaded from FRED. Standard deviations are reported in parentheses.

Table 3: Black-white gaps in UI generosity overall

	Overall		Extensive margin	Intensive margin	
	Weekly benefits	Replacement rate	Approved	Weekly benefits if approved	Replacement rate if approved
	(1)	(2)	(3)	(4)	(5)
Black-White Gap	-92.310***	-0.065***	-0.142***	-66.354***	0.003
	(3.599)	(0.004)	(0.006)	(3.673)	(0.005)
(i) Explained by State Rule differences	-30.724***	-0.030***	-0.068***	-13.023***	-0.014***
	(4.123)	(0.006)	(0.010)	(1.195)	(0.002)
(ii) Explained by Work History differences	-64.745***	-0.036***	-0.090***	-52.813***	0.020***
	(2.836)	(0.005)	(0.006)	(2.662)	(0.004)
(iii) Unexplained	3.159	0.001	0.016	-0.518	-0.003
	(3.866)	(0.006)	(0.011)	(1.745)	(0.003)
White mean	274.690	0.356	0.755	363.662	0.472
Gap/White mean	-0.336	-0.183	-0.188	-0.182	0.006
(i)/White mean	-0.112	-0.084	-0.090	-0.036	-0.030
(ii)/White mean	-0.236	-0.102	-0.119	-0.145	0.042
(iii)/White mean	0.012	0.003	0.021	-0.001	-0.006
Nb of observations	168,821	168,821	168,821	20,691	20,691

Notes: This Table presents the results from the decomposition of the racial gap in UI. The first line presents the size of the raw gap. The three lines below presents the size of the three components: (1) the gap explained by differences in state rules, (2) the gap explained by racial differences in work history (3) the unexplained gap (see section 4 for methods). In the bottom part of the Table, we present these gaps in relative terms, i.e. we divide each gap by the mean UI outcome for White claimants. In each column, we consider a specific UI outcomes: the weekly benefits amount (in $ per week), the replacement rate (in ppt), the eligibility rate (in ppt), the weekly benefits amount conditional on being eligible (in $ per week) and the replacement rate conditional on being eligible (in ppt). We present in parentheses bootstrapped standard errors obtained using 1000 iterations.

Table 4: Black-white gaps in UI generosity, only from monetary determinations

	Overall		Extensive margin	Intensive margin	
	Weekly benefits	Replacement rate	Approved	Weekly benefits if approved	Replacement rate if approved
	(1)	(2)	(3)	(4)	(5)
Black-White Gap	-76.477***	-0.034***	-0.082***	-59.541***	0.005
	(3.478)	(0.004)	(0.004)	(3.234)	(0.006)
(i) Explained by State Rule differences	-12.277***	-0.016***	-0.020***	-9.630***	-0.009***
	(2.025)	(0.003)	(0.006)	(1.424)	(0.002)
(ii) Explained by Work History differences	-64.037***	-0.017***	-0.070***	-48.689***	0.018***
	(3.276)	(0.004)	(0.005)	(2.905)	(0.005)
(iii) Unexplained	-0.163	-0.001	0.008	-1.222	-0.003*
	(1.908)	(0.003)	(0.006)	(1.191)	(0.002)
White mean	307.704	0.406	0.874	352.084	0.465
Gap/White mean	-0.249	-0.084	-0.094	-0.169	0.011
(i)/White mean	-0.040	-0.038	-0.023	-0.027	-0.020
(ii)/White mean	-0.208	-0.043	-0.080	-0.138	0.039
(iii)/White mean	-0.001	-0.002	0.009	-0.003	-0.007
Nb of observations	82,788	82,788	82,788	18,407	18,407

Notes: This Table presents the results from the decomposition of the racial gap in UI, arising from monetary determinations only. The first line presents the size of the raw gap. The three lines below presents the size of the three components: (1) the gap explained by differences in state rules, (2) the gap explained by racial differences in work history (3) the unexplained gap (see section 4 for methods). In the bottom part of the Table, we present these gaps in relative terms, i.e. we divide each gap by the mean UI outcome for White claimants. In each column, we consider a specific UI outcomes: the weekly benefits amount (in $ per week), the replacement rate (in ppt), the eligibility rate (in ppt), the weekly benefits amount conditional on being eligible (in $ per week) and the replacement rate conditional on being eligible (in ppt). We present in parentheses bootstrapped standard errors obtained using 1000 iterations.

ONLINE APPENDIX

A Data construction

A.1 Construction of sample of new claims

To make our sample representative of all new claims (or all new claimants), we build probability weights, i.e., weights equal to the inverse of the probability that a new claim is included in our sample. Because of the audit sampling procedure, the fraction of new claims in the population of paid claims and the fraction of new claims in the audit sample should be equivalent: all claims have an equal probability of being selected. Therefore, the probability of being in our restricted study sample is the same as the probability of selection in the audit sample: for each state s, week t and claim type c, it corresponds to $\frac{\#AuditAll_{cst}}{\#PopAll_{cst}}$, i.e., the size of the audit sample over the size of the population of ongoing claims. To see that, notice that the probability corresponds to:

$$\frac{\#AuditNew_{cst}}{\#PopNew_{cst}} = \frac{\#AuditNew_{cst}}{\frac{\#PopNew_{cst}}{\#PopAll_{cst}} \cdot \#PopAll_{cst}} = \frac{\#AuditNew_{cst}}{\frac{\#AuditNew_{cst}}{\#AuditAll_{cst}} \cdot \#PopAll_{cst}} = \frac{\#AuditAll_{cst}}{\#PopAll_{cst}}$$

Figure A.1: Validation checks:

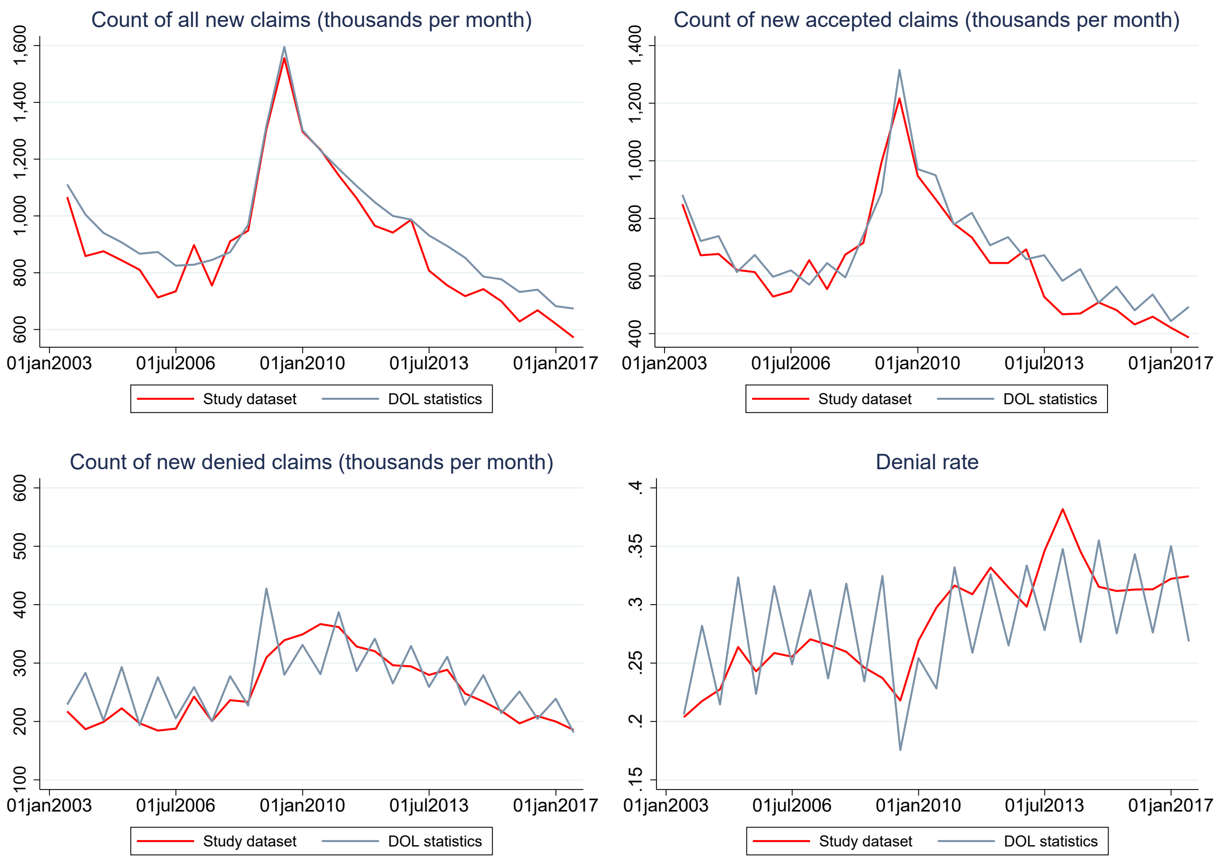


Table A.1: BAM vs. Administrative Information UI Claimants

	Full sample		Non-missing race	
	(1)	(2)	(3)	(4)
Variable	BAM	ETA	BAM	ETA
Sex				
Male	0.588	0.575	0.590	0.573
Female	0.412	0.422	0.410	0.424
Ethnicity				
Hispanic	0.169	0.154	0.056	0.048
Non-Hispanic	0.794	0.717	0.913	0.873
Unknown	0.037	0.129	0.031	0.079
Race				
White	0.715	0.571	0.698	0.676
Black	0.170	0.170	0.246	0.267
Asian	0.028	0.028	0.013	0.013
American Indian / Alaskan Native	0.012	0.012	0.013	0.015
Native Hawaiian / Oth. Pacific Islander	0.005	0.004	0.002	0.002
Multiple races	0.012	0.000	0.005	0.000
Race Unknown	0.057	0.215	0.022	0.024
Age				
<22	0.031	0.032	0.031	0.028
22-24	0.060	0.056	0.059	0.055
25-34	0.243	0.238	0.237	0.238
35-44	0.244	0.242	0.256	0.250
45-54	0.242	0.239	0.251	0.244
55-59	0.088	0.091	0.083	0.088
60-64	0.057	0.058	0.052	0.055
65+	0.036	0.038	0.030	0.034
Age unknown	0.000	0.006	0.000	0.009
Observations	354,934	599,460,640	114,773	147,679,968

Notes: Column (1) uses the entire sample of paid claim audits in the BAM data. Column (2) uses all state-month observations reported in the Department of Labor's ETA203 table. Columns (3) and (4) drop from both samples the state-year observations where the ETA203 table is missing race for over 5 percent of benefit weeks. Observations refers to the total number of benefit payments in the respective samples.

A.2 Validation of data construction

We compare the composition of paid claimants in the BAM sample to that of continuing claimants, available in the Department of Labor's ETA 203 report ("Characteristics of the Insured Unemployed").[22] The ETA 203 data provides counts of continuing claimants within several demographic categories. In most cases these are based on the full population of claimants since this information is collected at the application stage. Columns (1) and (2)

[22]For a discussion on the methodology of the ETA 203, and a comparison with the CPS unemployed population, see O'Leary, Spriggs, and Wandner (2021).

show demographic proportions for the full samples from both datasets for the time period under study and using all categories provided by the ETA 203 reports: sex, ethnicity, race, and age. In all columns, the observations at the bottom of the table refer to the total number of paid benefit weeks included in the sample. The shares suggest that the two sources align closely, with similar age and sex distributions. However, ethnicity and race information is often missing from the ETA 203 (O'Leary, Spriggs, and Wandner, 2021), so in columns (3) and (4) we remove state-years where more than 5 percent of benefit-weeks in the ETA 203 data were missing race. These adjusted samples also suggest highly similar composition along demographic dimensions.

A.3 Imputation of missing values

First imputation method A first data limitation affects denied claimants: for each denial type, the data only includes the work history variables necessary to determine the type of eligibility considered (either monetary or non-monetary eligibility).[23] We predict the variables relevant for monetary and separation eligibility for all claimants, by leveraging the correlation between each of these variables and other claimants' characteristics, in the subsamples where we observe them.

- For claims denied for a non-monetary reason, the BAM data does not report the variables used for monetary determinations: Base Period Earnings, Highest Quarter Earnings, Highest Quarter Earnings over Base Period Earnings and number of weeks worked during the base period. Fortunately, the data contains the wage in prior occupations for all claims. Therefore, we can predict the variables relevant for monetary determinations in the sample of eligible claimants and claimants denied for monetary reasons, based on the prior wage as well as the other variables observed for all claims: gender, age, occupation, industry, ethnicity and their interaction with race. Note that we include claims denied for monetary reasons, to observe the full distribution of the variables—not only values above the eligibility thresholds. We use the obtained coefficients to extrapolate predicted values for all claims.

- For claims denied for a monetary reason, the BAM data does not report the reason for separation. The dataset does not include straightforward way to proxy for this, but some separations might be more frequent in certain sectors, occupations, for certain wage categories, for certain demographic groups, in certain states. We hence predict the reason for separation based on this information, in the sample of claimants that are eligible, or monetarily eligible but denied for non-monetary reasons. We use the obtained coefficients to extrapolate predicted values for all claims.

[23] This means that, for claims denied for a non-monetary reason, we don't observe the variables used for monetary determinations ; and for claims denied for a monetary reason, we don't observe the reason for separation.

This method provides us with a set of proxies for all work history characteristics. We will use these proxies in the analyses conducted on the full sample of claimants.

Second imputation method A second data limitation concerns both eligible and denied claimants, in 10% of state-years. The BAM data only includes monetary variables that were relevant to determine the claimant's eligibility: in 90%, these are the Base Period Earnings and the Highest Quarter Earnings; but in 10% of state-years, Highest Quarter Earnings are not considered, and Base Periods Earnings are either considered alone or in combination with Weeks Worked (see Section 2.1). In the sample of eligible claimants, we predict the Highest Quarter Earnings and Weeks Worked for all state-years, by leveraging the correlation between each of these variables and other claimants' characteristics (Base Period Earnings, prior wage, gender, age, occupation, industry, ethnicity and their interaction with race) in the subsamples of state-years that include them. We use the obtained coefficients to extrapolate predicted values in states that do not report these variables, in the sample of eligible claims.

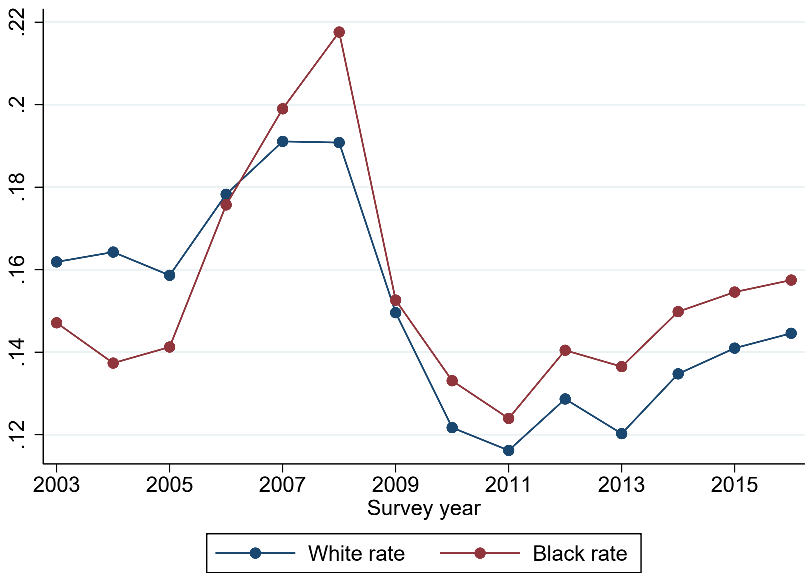
This second method provides us with a second set of proxies for some of the work history characteristics (Highest Quarter Earnings and Weeks Worked), for the sample of eligible claimants. They are likely better proxies than those obtained using the first method, as they also make use of information on the Base Periods Earnings. We will use these proxies in the analyses conducted on the sample of claimants, for the sample of eligible claimants.

A.4 Discussion of UI claiming rates measures

Measuring claiming rate using BAM and CPS data Our administrative UI data provides reliable estimates of the national counts of applicants and recipients across demographic groups, as in Table 1. However, it is not possible to exactly measure to appropriate denominator for calculating a claiming rate. We list a few potential problems here. First, we don't observe the date of the job separation for all claims in the BAM data, so we cannot directly map claimants to job separations in the CPS. Claims appear to be made most frequently in the first few months after job separations, but the delays could differ across demographic groups. Second, we cannot attribute to claimants in the BAM data the same type of labor market status that is reported in the CPS. In principle, people might claim UI when they are only marginally attached to the labor force—even if, in practice, it is likely that new claims come from workers who are unemployed. Moreover, demographic categories could be constructed differently in the two data sources (this could explain why CPS respondents do not report their race being unknown, while 5% of BAM claimants do), which could bias cross-group comparisons.

In the end, we build a tentative claiming rate, by taking the ratio of the count of new claim over the count of unemployed people, as it appears like a natural benchmark. But we note that the claiming rate that we obtain might be biased, and that the bias could differ across demographic groups. Differences in claiming rates across groups should hence be interpreted with caution.

Figure A.2: Ratio of BAM claimants over CPS unemployed



Claiming rates by race We present the claiming rates obtained by taking the ratio of BAM new claimants over CPS unemployed, by race, in Figure A.2. Specifically, since CPS is a monthly survey, we take the count of new claimants each month (from BAM) over the count of unemployed each month (from the CPS), then take the yearly average. We hence measure the fraction of all unemployed who claim UI in a month. The plot suggests that the share of unemployed people who claim UI is quite similar across races over our sample period. It is actually slightly lower for Black unemployed workers before 2006, and slightly higher after 2006. Interestingly, this is in line with the finding in Gould-Werth and Shaefer (2012, Table 1), that the claiming rate is lower for Black unemployed workers in 2005. Using using the 2005 CPS Non-filer supplement, the authors find that 38.4% of unemployed Blacks and 49.5% of unemployed whites apply for UI. We note however that those two sources measure something very different: our ratio captures the applications sent solely in a given month ; while the CPS Non-filer is a backward-looking measure, detecting for each individual any claim that happened at any time of the spell. It is therefore not surprising that the orders of magnitude are different.

B Empirical strategy

B.1 Decomposition of the racial gap in UI receipt

From the expression of statutory UI outcome in equation 2, let's derive the average statutory UI outcome for all people over one race group (Black or White). Let $g \in \{b, w\}$ denote the group index, N_g denote the number of people in the group overall, and $N_{g,k}$ the number of people in the group in each state. Capital letters refer to claimant populations: G denotes the claimant population of group g, K denotes the claimant population of state k. Overlines denote the average of one variable over one population.

$$
\begin{aligned}
\overline{UI_g^*} &= \frac{1}{N_g} \sum_{i \in G} UI_i^* \\
&= \frac{1}{N_g} \sum_{i \in G} \left(\overline{\alpha}_0 + X_i \overline{\alpha}_1 + \sum_k \left(S_{i,k} \cdot X_i \widetilde{\alpha}_{1,k} + S_{i,k} \cdot \widetilde{\alpha}_{0,k} \right) \right) \\
&= \overline{\alpha}_0 + \frac{1}{N_g} \sum_{i \in G} X_i \overline{\alpha}_1 + \frac{1}{N_g} \sum_{i \in G} \sum_k \left(S_{i,k} \cdot X_i \widetilde{\alpha}_{1,k} + S_{i,k} \cdot \widetilde{\alpha}_{0,k} \right) \\
&= \overline{\alpha}_0 + \overline{X_g} \overline{\alpha}_1 + \frac{1}{N_g} \sum_k \left(\sum_{i \in G, i \in K} (X_i \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) + \sum_{i \in G, i \notin K} 0 \right) \\
&= \overline{\alpha}_0 + \overline{X_g} \overline{\alpha}_1 + \sum_k \left(\frac{N_{g,k}}{N_g} \cdot \overline{X_{g,k}} \cdot \widetilde{\alpha}_{1,k} + \frac{N_{g,k}}{N_g} \cdot \widetilde{\alpha}_{0,k} \right) \\
&= \overline{\alpha}_0 + \overline{X_g} \overline{\alpha}_1 + \sum_k \left(\overline{S_{g,k}} \cdot \overline{X_{g,k}} \cdot \widetilde{\alpha}_{1,k} + \overline{S_{g,k}} \cdot \widetilde{\alpha}_{0,k} \right)
\end{aligned}
$$

So the gap between the average statutory UI outcomes between black and white claimants can be written as:

$$
\overline{UI_b^*} - \overline{UI_w^*} = (\overline{X_b} - \overline{X_w}) \overline{\alpha}_1 + \sum_k \left((\overline{S_{b,k}} \cdot \overline{X_{b,k}} - \overline{S_{w,k}} \cdot \overline{X_{w,k}}) \cdot \widetilde{\alpha}_{1,k} + (\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot \widetilde{\alpha}_{0,k} \right) \quad \text{(B.1)}
$$

B.2 Detailed decomposition

Here we present formally the more detailed decomposition of the gap between the average statutory UI outcomes between black and white claimants. We can re-arrange the expression of the gap in equation (B.1), in order to show its sub-components:

$$\begin{aligned}
\overline{UI_b^*} - \overline{UI_w^*} &= (\overline{X_b} - \overline{X_w})\overline{\alpha}_1 + \sum_k \left((\overline{S_{b,k}} \cdot \overline{X_{b,k}} - \overline{S_{w,k}} \cdot \overline{X_{w,k}}) \cdot \widetilde{\alpha}_{1,k} + (\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot \widetilde{\alpha}_{0,k} \right) \\
&= (\overline{X_b} - \overline{X_w})\overline{\alpha}_1 + \sum_k \left(\left((\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot \overline{X_{b,k}} + (\overline{X_{b,k}} - \overline{X_{w,k}}) \cdot \overline{S_{w,k}} \right) \widetilde{\alpha}_{1,k} + (\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot \widetilde{\alpha}_{0,k} \right) \\
&= (\overline{X_b} - \overline{X_w})\overline{\alpha}_1 + \sum_k \left((\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot (\overline{X_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) \right) + \sum_k \left((\overline{X_{b,k}} - \overline{X_{w,k}}) \cdot \overline{S_{w,k}} \cdot \widetilde{\alpha}_{1,k} \right)
\end{aligned} \tag{B.2}$$

This expression highlights that the differences in UI rules across states can influence the gap in unemployment insurance through two channels. First, Blacks are disadvantaged when rules are stricter ($(\overline{X_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k})$ is negative) in states where a larger fraction of all Black claimants live relative to the fraction of all White claimants ($(\overline{S_{b,k}} - \overline{S_{w,k}})$ is positive). Second, Blacks are disadvantaged when the impact of work history characteristics is larger ($\widetilde{\alpha}_{1,k}$ is positive) in states where they have worse work history characteristics than White claimants ($(\overline{X_{b,k}} - \overline{X_{w,k}})$ is negative).

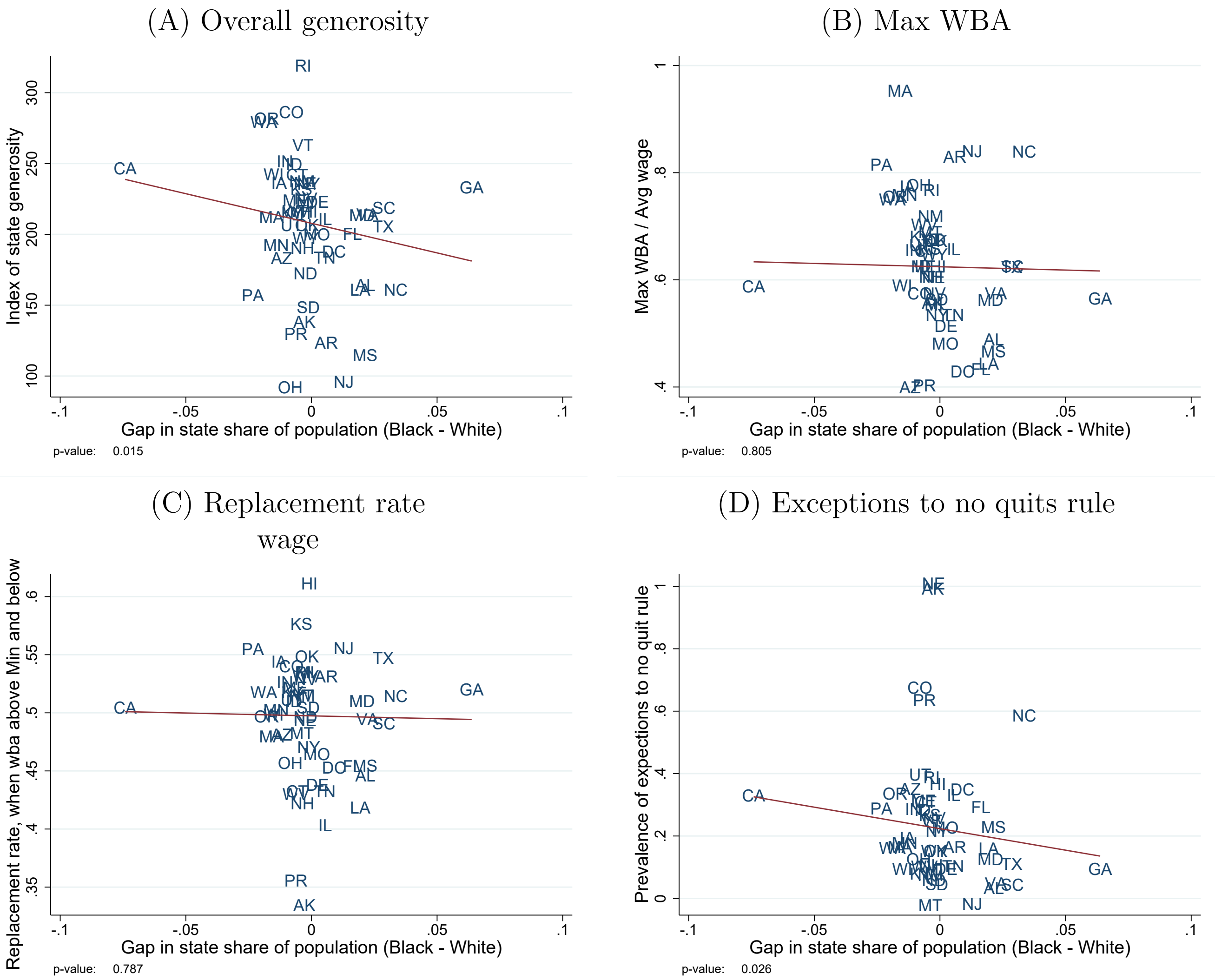
C Additional descriptive statistics

Table C.1: Description of state rules

	Count	Mean	Median	SD	Min	Max	Corr
Benefits amount, for those eligible							
Max WBA / Avg wage	52	0.63	0.59	0.12	0.40	0.97	-0.22
Prop recipents at Max WBA	52	0.32	0.32	0.15	0	0.68	0.31**
Min WBA / Avg wage	52	0.092	0.09	0.035	0.023	0.19	-0.03
Prop recipents at Min WBA	52	0.0042	0.00	0.016	0	0.11	-0.21
Replacment rate, if WBA $\in]$Min,Max$[$	52	0.78	0.75	0.11	0.50	1.17	-0.24*
Benefits duration, for those eligible							
Max Duration	52	25.8	26.00	0.93	24.1	30	-0.40***
Eligibility determination							
Min required BPE / Avg wage	52	0.082	0.08	0.035	0.022	0.16	0.21
Possibility of eligibility for job quitters	52	0.23	0.20	0.15	0	1.00	-0.30**
Overall generosity							
Index of overall generosity	52	211.1	216.06	43.0	91.9	319.2	-0.34**

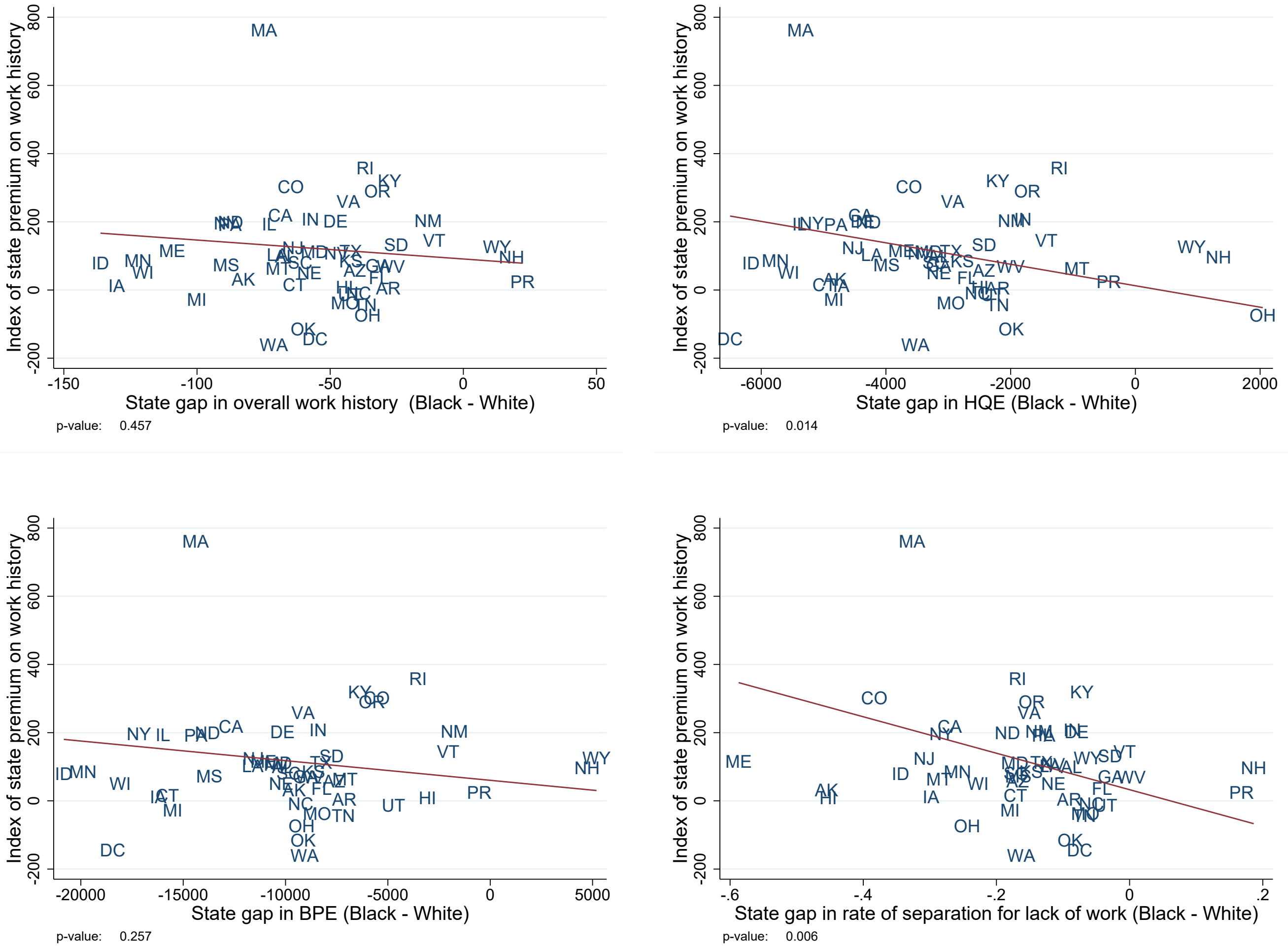
Notes: This Table presents summary statistics on various dimensions of UI rules at the state level, where each state is weighted by its number of claimants. The state rule variables are: the statutory maximum level of weekly benefits, the share of people receiving the max WBA, the statutory minimum level of benefits, the multiplicative term in the benefit calculation for eligible claimants that receive a WBA above the min and below the maximum, the maximum number of weeks people can claim UI in a spell, the lowest base period earnings required to be monetary eligible, the proportion of claimants quitting their jobs who are eligible, an index we build to summarize all dimensions of state rules generosity (see Section 5.3). All earnings variable are normalized by the average prior wage earned by claimants in the state, to account for differences in price levels across states. Note that all variables measure the generosity of UI rules to claimants except for two, which instead measure the strictness of the rules: the proportion of recipients at Max WBA, and the min required BPE for eligibility. In the Corr column, we show the correlation between the UI rule variable and the share of UI claimants who are Black, with $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.10$.

Figure C.1: Correlation between various measures of state rules generosity, and the racial gap in the share of claimants



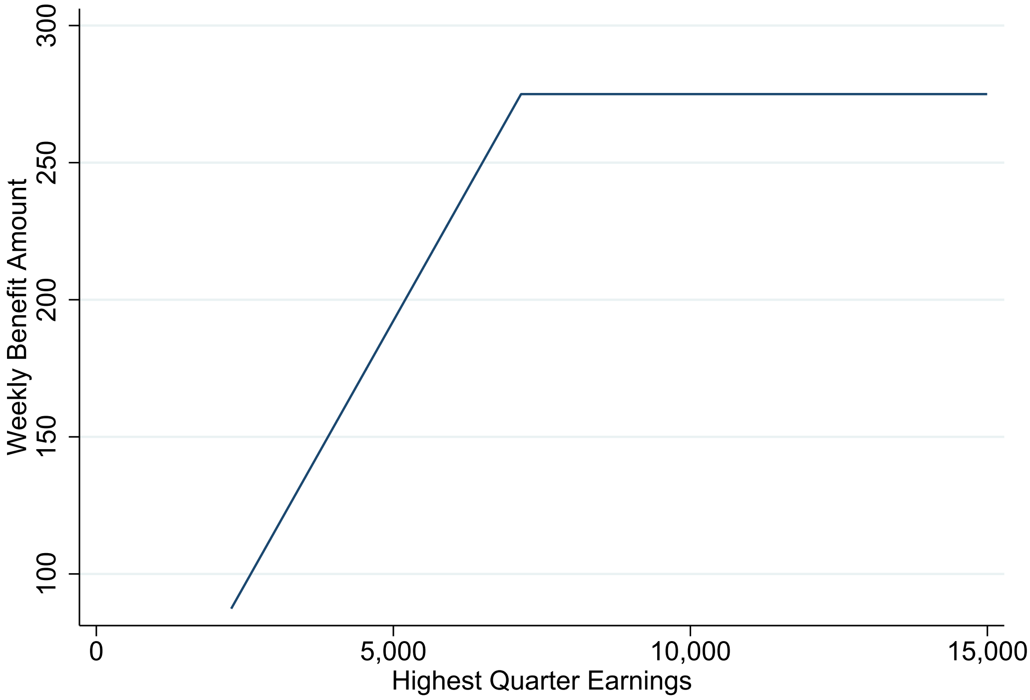
Note: This Figure presents the correlation of state rule generosity and the importance of the Black population in the state level, measured using the difference between the share of Black claimants who leave in the state minus the share of White claimant who live in the state. We measure state generosity using an index summarize all dimensions of state rules in Panel (A) (see Section 5.3) ; the statutory maximum level of weekly benefits in Panel (B) ; the multiplicative term used to compute weekly benefits (WBA over weekly BPE) for claimants who receive a WBA above the minimum and below the maximum in Panel (C) ; the proportion of claimants quitting their jobs who are eligible in Panel (D). All earnings variable are normalized by the prior average wage earned by claimants in the state, to account for differences in price levels across states. We present the regression line and the corresponding p-value, obtained when each state is weighted by its number of claimants.

Figure C.2: Correlation between the index of state premium on work history characteristics, and various measures of racial gap in work history characteristics



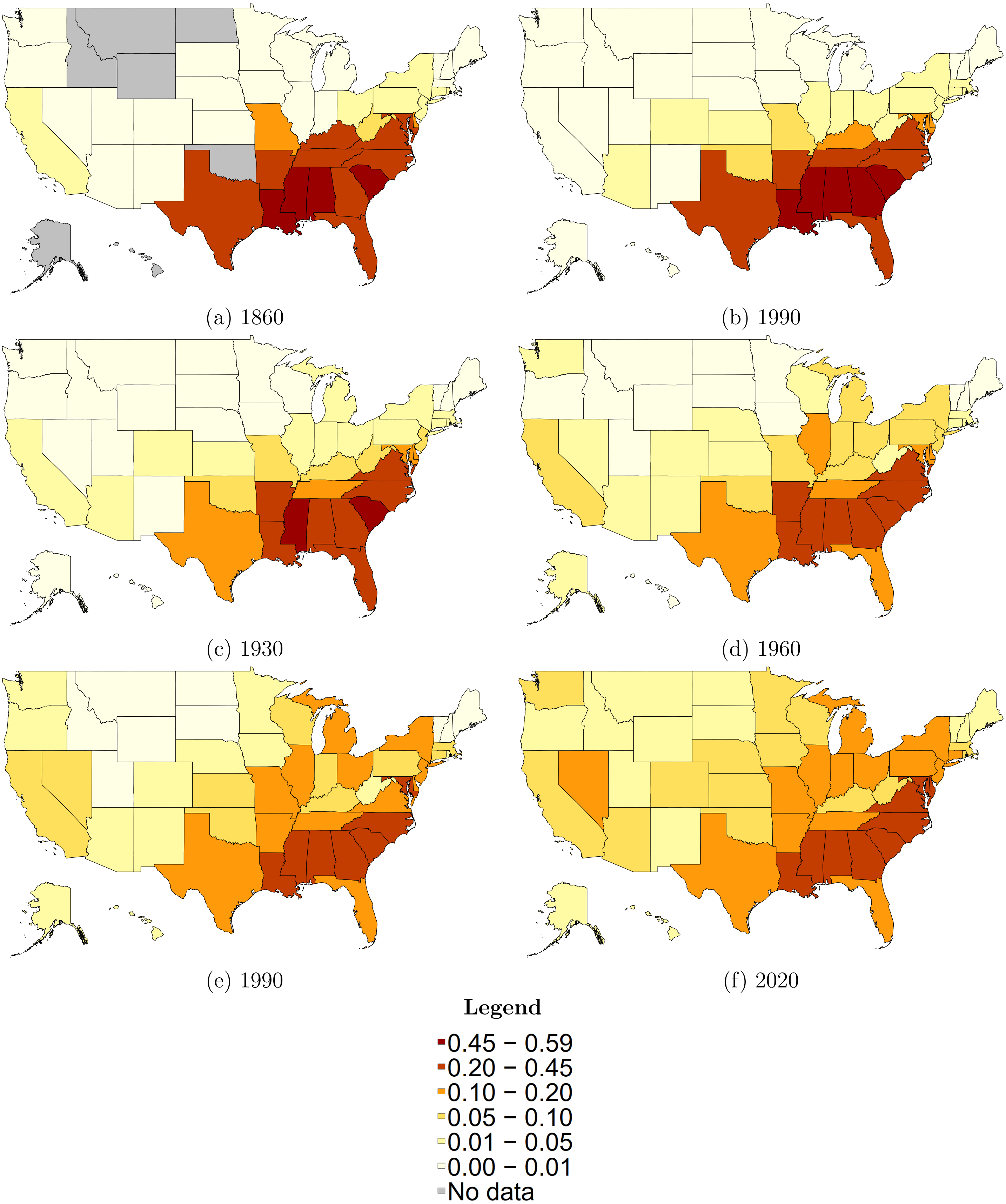
Note: In all panels, we present in the y-axis the Index of overall generosity, over the average prior wage of claimants in the state (see Section 5.3). Each panel presents a specific measure of the gap in work history characteristics in the x-axis. We present the regression line and the corresponding p-value, obtained when each state is weighted by its number of claimants.

Figure C.3: Weekly benefit amount formula, Florida 2015



Note: This plot gives an example of the most common formula (the "high-quarter method") for calculating the weekly benefit amount, using the Florida entitlement rules as of 2015. The y-axis gives the weekly benefit amount and the x-axis gives the claimant's highest quarter earnings, taken from the base period quarter in which earnings were highest. Weekly benefits are given by (1/26) times highest quarter earnings, until the maximum of \$275. Highest quarter earnings need to be at least \$2,267 to qualify.

Figure C.4: Historical Black shares



(a) 1860

(b) 1990

(c) 1930

(d) 1960

(e) 1990

(f) 2020

Notes: This figure shows historical Black share the population for all states from 1860 to 2020. The source data is Census Bureau estimates (Gibson and Jung, 2002).

D Robustness checks and additional results

Table D.1: Black-white gaps in UI generosity overall - Estimating state rules with machine learning

	Overall		Extensive margin	Intensive margin	
	Weekly benefits	Replacement rate	Approved	Weekly benefits if approved	Replacement rate if approved
	(1)	(2)	(3)	(4)	(5)
Black-White Gap	-92.406***	-0.065***	-0.142***	-66.392***	0.003
	(3.586)	(0.004)	(0.006)	(3.343)	(0.005)
(i) Explained by State Rule differences	-43.982***	-0.049***	-0.089***	-13.705***	-0.015***
	(3.389)	(0.005)	(0.006)	(1.558)	(0.002)
(ii) Explained by Work History differences	-55.398***	-0.017***	-0.088***	-53.604***	0.018***
	(2.623)	(0.004)	(0.004)	(2.956)	(0.004)
(iii) Unexplained	6.975**	0.000	0.035***	0.917	0.000
	(3.342)	(0.007)	(0.007)	(0.805)	(0.001)
White mean	274.776	0.417	0.756	363.700	0.474
Gap/White mean	-0.336	-0.156	-0.188	-0.183	0.007
(i)/White mean	-0.160	-0.117	-0.118	-0.038	-0.032
(ii)/White mean	-0.202	-0.040	-0.117	-0.147	0.038
(iii)/White mean	0.025	0.001	0.047	0.003	0.001
Nb of observations	168,821	168,821	168,821	20,691	20,691

Notes: This table shows the point estimates and standard errors of the same decomposition shown in Table 3, except in these calculations we used the random forests algorithm, fit using white claimants, to estimate how outcomes (weekly benefits, approval, etc.) vary with work history in each state. The state-level hyperparameters were chosen using 150 iterations of a random grid search with 5-fold validation. The standard errors are calculated using a bootstrap with 50 iterations, in each case using the same set of optimal hyperparameters from the initial grid search.

Table D.2: Robustness checks: Black-white gaps in monetary determinations, using proxies or actual variables to control for claimants' work history

	Proxies (first type)		Proxies (second type)		Actual variables	
	Weekly benefits	Replacement rate	Weekly benefits	Replacement rate	Weekly benefits	Replacement rate
	(1)	(2)	(3)	(4)	(5)	(6)
Black-White Gap	-76.477***	-0.034***	-76.477***	-0.034***	-76.477***	-0.034***
	(2.952)	(0.004)	(2.952)	(0.004)	(2.952)	(0.004)
(i) Explained by State Rule differences	-15.670***	-0.019***	-13.498***	-0.019***	-12.277***	-0.016***
	(2.566)	(0.004)	(1.000)	(0.002)	(1.853)	(0.003)
(ii) Explained by Work History differences	-59.282***	-0.011***	-64.575***	-0.018***	-64.037***	-0.017***
	(2.502)	(0.004)	(2.855)	(0.004)	(2.902)	(0.004)
(iii) Unexplained	-1.524	-0.003	1.596	0.003	-0.163	-0.001
	(2.469)	(0.004)	(1.270)	(0.003)	(1.700)	(0.003)
White mean	310.273	0.410	310.273	0.410	310.273	0.410
Gap/White mean	-0.246	-0.083	-0.246	-0.083	-0.246	-0.083
(i)/White mean	-0.051	-0.047	-0.044	-0.047	-0.040	-0.038
(ii)/White mean	-0.191	-0.028	-0.208	-0.043	-0.206	-0.043
(iii)/White mean	-0.005	-0.008	0.005	0.007	-0.001	-0.002
Nb of observations	82,788	82,788	82,788	82,788	82,788	82,788

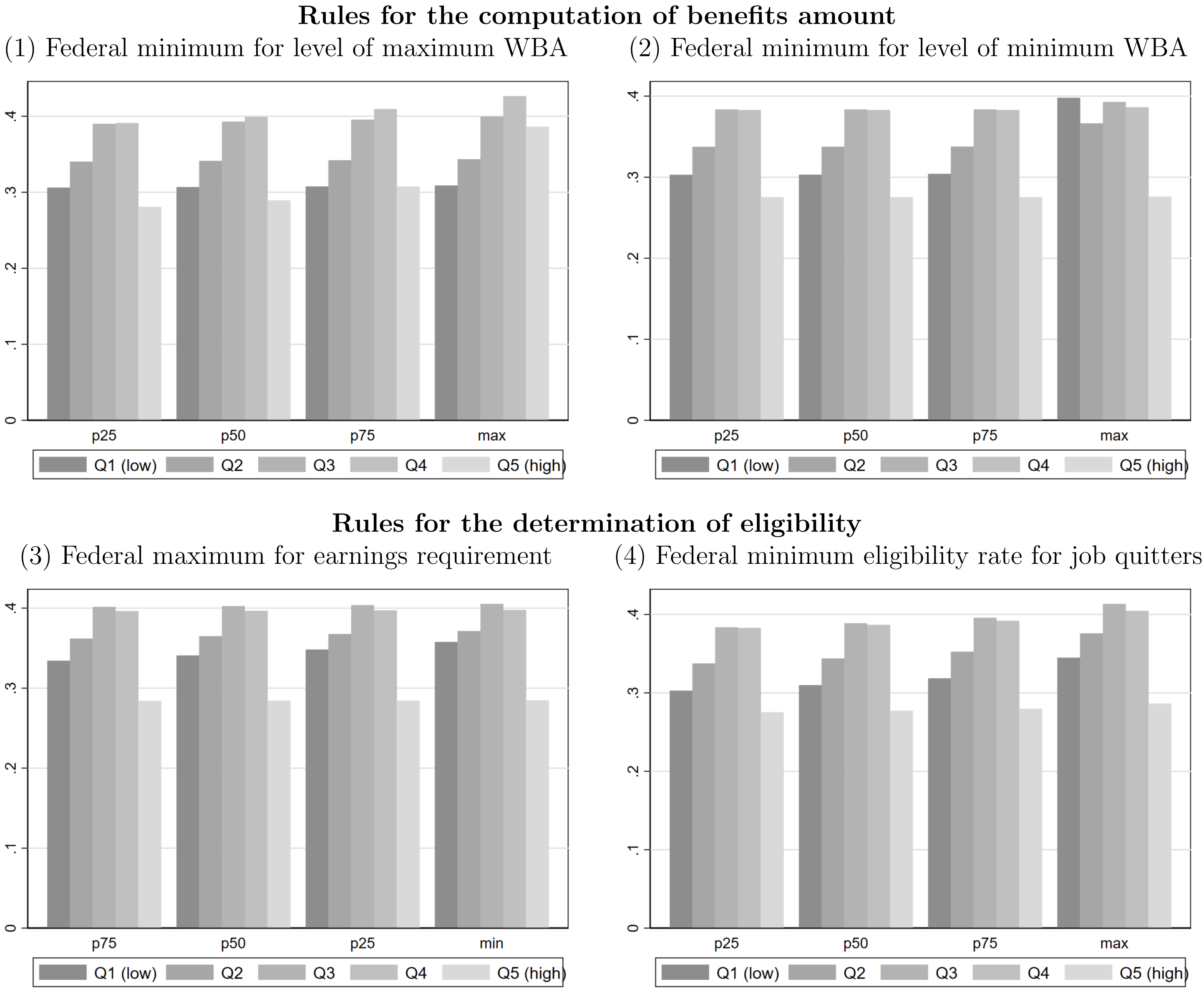
Notes: In this Table, we present the same estimates as in the first two columns of Table 4, except that we use proxy for monetary work history variables in columns (1) to (4). In columns (1) and (2), we use a first set of proxies based on claimants characteristics (). In columns (3) and (4), we use a second set of proxies obtained based on claimants characteristics and claimants Base Period Earnings. For more details on the two types of proxies, see Appendix A.3. In columns (5) and (6), we present for comparison the results obtained when using the actual monetary work history variables instead of proxies (the estimates are hence the same as those presented in the first two columns of Table 4.

Table D.3: Robustness checks: Black-white gaps in UI, controlling for demographic characteristics

	Overall		Extensive margin	Intensive margin	
	Weekly benefits	Replacement rate	Approved	Weekly benefits if approved	Replacement rate if approved
	(1)	(2)	(3)	(4)	(5)
Black-White Gap	-92.310***	-0.065***	-0.142***	-66.354***	0.003
	(4.145)	(0.005)	(0.008)	(3.351)	(0.004)
(i) Explained by State Rule differences	-32.969***	-0.034***	-0.077***	-13.119***	-0.014***
	(3.463)	(0.007)	(0.010)	(1.761)	(0.003)
(ii) Explained by Individual characteristics differences	-64.618***	-0.036***	-0.089***	-52.581***	0.021***
	(2.566)	(0.005)	(0.007)	(3.027)	(0.004)
(iii) Unexplained	5.277	0.006	0.023**	-0.654	-0.003
	(3.703)	(0.007)	(0.010)	(2.495)	(0.005)
White mean	274.690	0.356	0.755	363.662	0.472
Gap/White mean	-0.336	-0.183	-0.188	-0.182	0.006
(i)/White mean	-0.120	-0.097	-0.102	-0.036	-0.030
(ii)/White mean	-0.235	-0.102	-0.117	-0.145	0.043
(iii)/White mean	0.019	0.015	0.031	-0.002	-0.007
Nb of observations	168,821	168,821	168,821	20,691	20,691

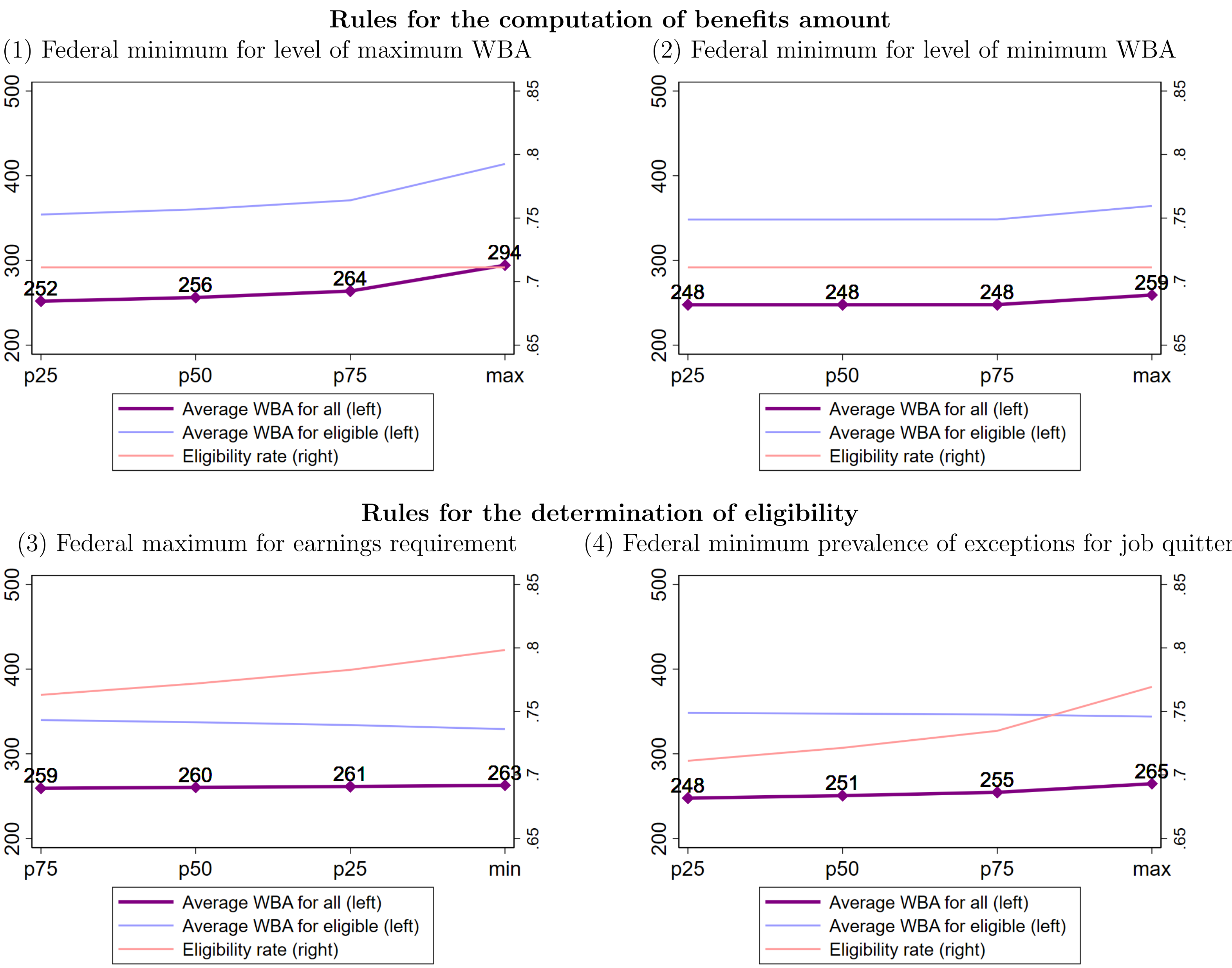
Notes: In this Table, we present the same estimates as in Table 3, except that component (ii) does not only capture the role of differences in Work history variables, but also in demographic variables: gender, age, education level. As these demographic variables are a priori not relevant for UI, we expect that the results should not be affected by their inclusion.

Figure D.1: Policy simulation



Notes: We present the simulated replacement rate for claimants with prior wages in different quintiles of the prior wage distribution, under different hypothetical policy reforms. We consider the same policy reforms as in Figure D.1: we harmonize the cap on WBA (in (1)), the minimum level of WBA (in (2)), the minimum BPE required for eligibility (in (3)), and the rate of eligibility for job quitters (in (4)).

Figure D.2: Policy simulation

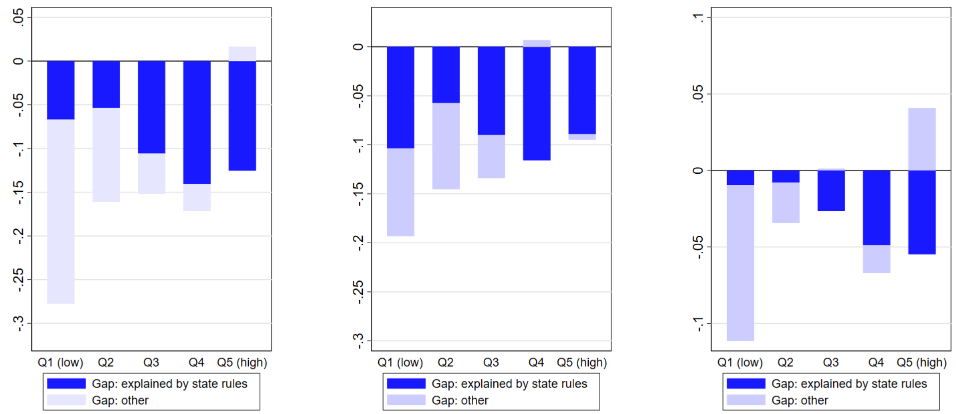


Notes: In this Figure, the thick line represents the simulated average weekly benefits amount among all UI claimants, under different hypothetical policy reforms. We also present the simulated average weekly benefits amount among eligible claimants, and the simulated eligibility rate. We consider the same policy reforms as in Figure D.1: we harmonize the cap on WBA (in (1)), the minimum level of WBA (in (2)), the minimum BPE required for eligibility (in (3)), and the rate of eligibility for job quitters (in (4)).

Figure D.3: Heterogeneity of the racial gaps, across prior wage quintile

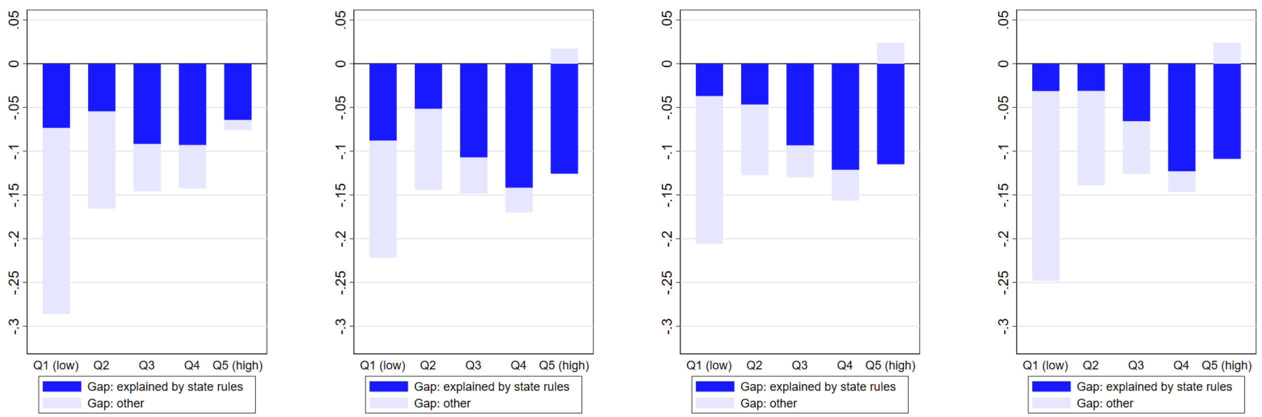
A/ Actual gap, in various outcomes:

(A.1) Replacement rate (A.2) Eligibility (A.3) Replacement rate if eligible



B/ Simulated gap in replacement rate, with harmonized:

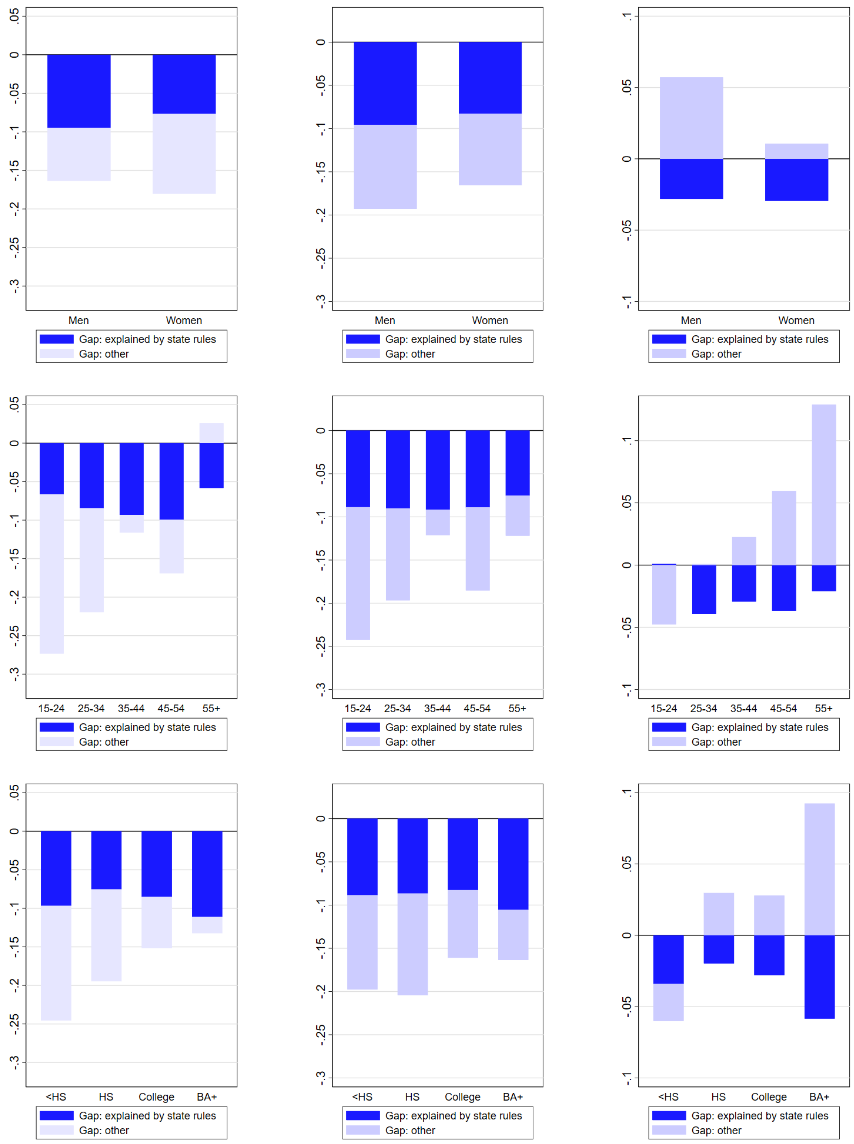
(B.1) Max WBA (B.2) Min WBA (B.3) Required BPE (B.4) No-quit exception



Note: In the upper part, we present the Black-White gaps explained by state rules differences for three outcomes: replacement rate, eligibility (extensive margin), replacement rate if eligible (intensive margin). In the lower part, we present the gap in replacement rate obtained if we harmonized each of the four policy parameter considered (set to the maximum generosity level). The y-axes always represent the magnitude of the relative gaps in %. We show separately the gaps for claimants in various quintiles of the distribution of hourly wage before job loss (below \$10.7, 10.7-13.9, 13.9-18.1, 18.1-25.9, above \$25.9).

Figure D.4: Heterogeneity in the racial gaps, across gender, age, education groups

(1) Replacement rate (2) Eligibility (3) Replacement rate if eligible

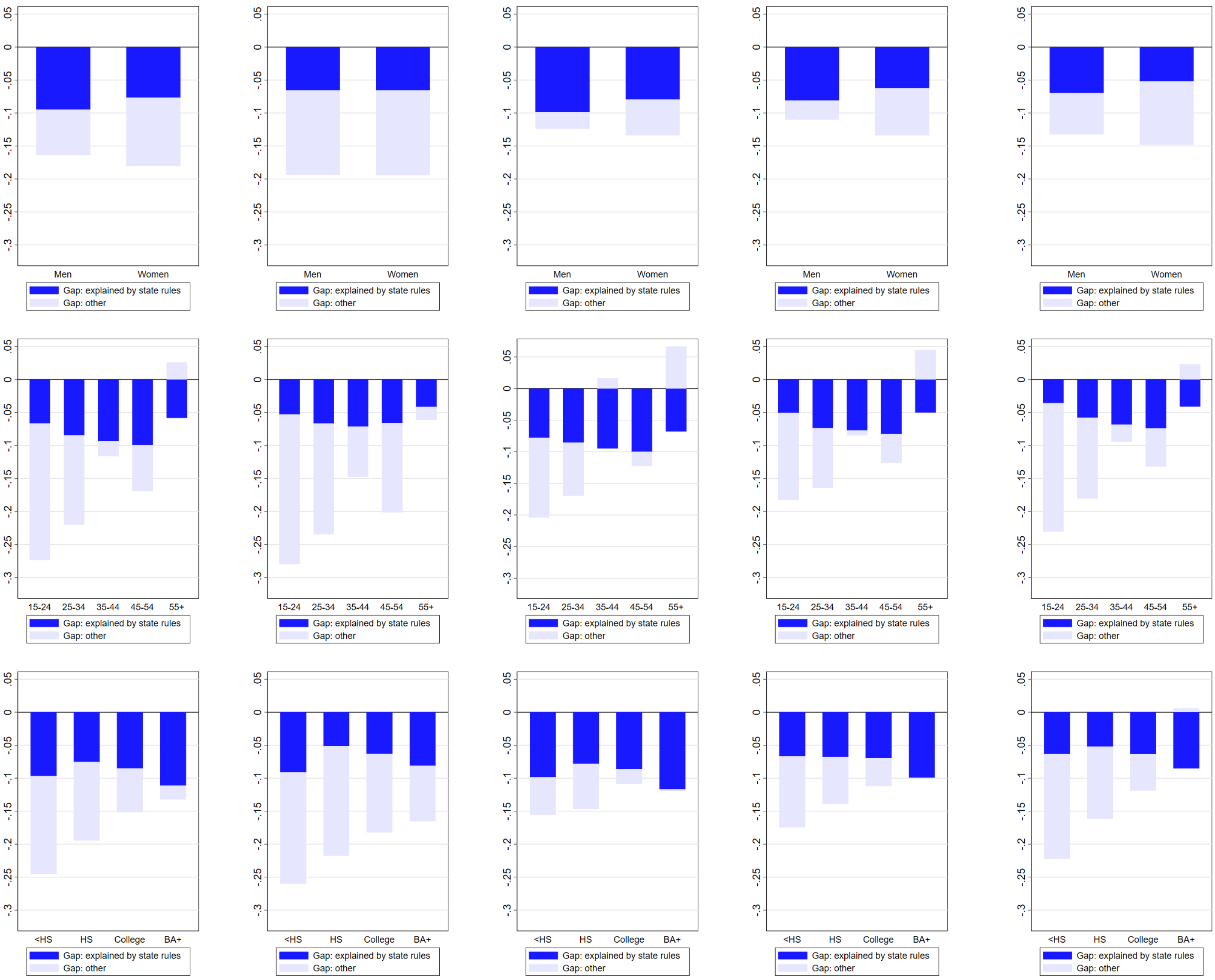


Note: We present the Black-White gaps explained by state rules differences for three outcomes: replacement rate, eligibility (extensive margin), replacement rate if eligible (intensive margin). The y-axis represent the magnitude of the relative gaps in %. We show separately the gaps for men and women, for claimants in different age groups, with different education levels (less than high school degree, high school degree, attended college, bachelor degree or above).

Figure D.5: Heterogeneity in the actual and simulated racial gaps, across gender, age, education groups

Actual gap | **Simulated gap, with harmonized:**

(1) | (2) Max WBA | (3) Min WBA | (4) Required BPE | (5) No-quit exception



Note: We present the Black-White gaps in replacement rate. The y-axis represent the magnitude of the relative gaps in %. We show separately the gaps for men and women, for claimants in different age groups, with different education levels (less than high school degree, high school degree, attended college, bachelor degree or above).

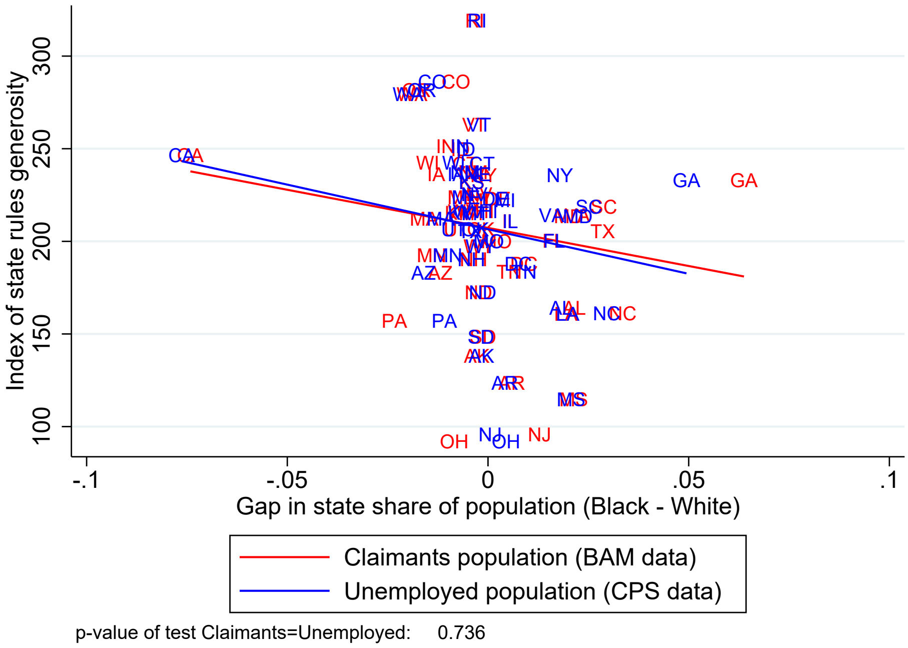
Table D.4: Mistakes (original value - value determined after BAM audit) in the assessment of UI outcomes and work history variables

	WBA			Replacement rate			Base period earnings			Highest quarter earnings			Separated for lack of work		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Black	-1.608	-0.191	-1.050	-0.007***	-0.001	-0.003*	-5.077***	-2.981***	-2.334**	3.142***	1.993***	2.136***	0.008	0.001	0.005
	(1.019)	(1.415)	(0.781)	(0.002)	(0.002)	(0.002)	(0.920)	(0.843)	(1.000)	(0.387)	(0.332)	(0.302)	(0.005)	(0.005)	(0.005)
Not Black nor White	-5.545**	-5.623**	-2.944**	-0.017**	-0.016**	-0.013	-3.091*	-2.305	-3.710**	0.916*	0.421	0.208	0.015	0.011	0.014
	(2.267)	(2.358)	(1.289)	(0.008)	(0.008)	(0.008)	(1.713)	(1.536)	(1.476)	(0.520)	(0.439)	(0.289)	(0.010)	(0.008)	(0.009)
Female		2.286***	2.100***		-0.001	-0.001		1.253*	1.450**		1.992***	1.996***		-0.001	-0.001
		(0.389)	(0.370)		(0.002)	(0.002)		(0.654)	(0.632)		(0.170)	(0.172)		(0.005)	(0.005)
Age: 25-34		-2.070	-2.501		-0.004	-0.005		4.141***	4.016***		-3.394***	-3.333***		-0.008	-0.007
		(1.411)	(1.579)		(0.004)	(0.004)		(1.247)	(1.157)		(0.331)	(0.365)		(0.008)	(0.009)
Age: 35-44		-2.331	-2.782*		0.000	-0.000		6.137***	5.998***		-4.372***	-4.335***		-0.016*	-0.015
		(1.466)	(1.565)		(0.002)	(0.002)		(1.480)	(1.428)		(0.291)	(0.304)		(0.009)	(0.009)
Age: 45-54		-1.243	-1.674		0.002	0.002		7.026***	6.838***		-4.745***	-4.664***		-0.021*	-0.022*
		(1.119)	(1.116)		(0.002)	(0.002)		(1.296)	(1.251)		(0.294)	(0.291)		(0.011)	(0.012)
Age: $\geq$ 55		0.527	-0.148		0.006***	0.005**		5.769***	5.663***		-3.856***	-3.751***		-0.012	-0.013
		(1.365)	(1.616)		(0.002)	(0.002)		(1.743)	(1.642)		(0.350)	(0.356)		(0.011)	(0.011)
Educ: HS degree		-0.889	-1.872		-0.003	-0.004		-0.060	0.503		-0.290	0.000		-0.009	-0.012
		(0.915)	(1.616)		(0.003)	(0.003)		(0.828)	(0.856)		(0.351)	(0.387)		(0.008)	(0.009)
Educ: Some college		-3.654**	-3.880*		-0.003	-0.003		0.584	0.632		-0.992**	-0.784**		-0.011*	-0.013**
		(1.802)	(2.009)		(0.002)	(0.003)		(1.090)	(1.087)		(0.408)	(0.386)		(0.006)	(0.006)
Educ: College degree		-2.849*	-3.699*		0.002	0.001		1.312	1.073		-1.127**	-0.832*		0.005	0.002
		(1.483)	(1.983)		(0.001)	(0.002)		(1.086)	(0.977)		(0.440)	(0.495)		(0.007)	(0.007)
Occup & Ind FE		×	×		×	×		×	×		×	×		×	×
State FE			×			×			×			×			×
N	194,481	194,472	194,472	194,420	194,411	194,411	108,353	108,349	108,349	98,609	98,605	98,605	91,130	91,121	91,121

Notes: This table presents the correlation of mistakes in the assessment of UI outcomes or of work history variables and claimants' characteristics. For each variable, we measure mistakes by taking the original value minus the value determined at the end of the BAM audit: if the mistake is positive, it means that the variables was overestimated by UI officer (relative to the value determined by the auditors). Positive mistakes for all the considered variables are favorable to claimants. We consider two types of mistakes in UI outcomes: mistakes in weekly benefits amount, and in replacement rate. We consider three types of mistakes in work history variables: mistakes in the Base period earnings (divided by yearly prior wage: $52 \times 40 \times$ prior hourly wage), mistakes in the Highest quarter earnings (divided by quarterly prior wage: $13 \times 40 \times$ prior hourly wage), mistakes in the determination that claimants separated from their prior job due to lack of work (i.e. involuntarily and for no fault of their own). We report robust standard errors clustered at the state level.

Figure D.6: Characteristics of Black and White workers across states, in the population of claimants and in the population of unemployed

(1) State rules generosity and racial gap in state representation, in the population of claimants and in the population of unemployed



(2) State rules generosity and racial gap in prior wage, in the population of claimants and in the population of unemployed

Notes: In Graph (1), we compare the correlation between state generosity in UI rules and the gap in the representation of Black and White claimants in the state, in the population of UI claimants (in red) and in that of unemployed workers (in blue). In Graph (2), we compare the correlation between state generosity in UI rules and the gap in the prior wage of Black and White claimants in the state, in the population of UI claimants (in red) and in that of unemployed workers (in blue). Under each graph, we report the p-value for the statistical test that the correlations in the two samples are equal.

E Discussion of claiming patterns, for Black and White unemployed workers

E.1 Racial gap among unemployed workers

We have shown (in formulas (3) and (4)) that the gap among claimants can be written as:

$$\overline{UI_b^*} - \overline{UI_w^*} = (\overline{X_b} - \overline{X_w})\overline{\alpha}_1 + \sum_k \Big((\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot (\overline{X_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) + (\overline{X_{b,k}} - \overline{X_{w,k}}) \cdot \overline{S_{w,k}} \cdot \widetilde{\alpha}_{1,k} \Big)$$

Similarly, the gap among unemployed can be written as (with the superscript u standing for the sample means in the population of unemployed workers):

$$\overline{UI_b^u} - \overline{UI_w^u} = (\overline{X_b^u} - \overline{X_w^u})\overline{\alpha}_1 + \sum_k \Big((\overline{S_{b,k}^u} - \overline{S_{w,k}^u}) \cdot (\overline{X_{b,k}^u} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) + (\overline{X_{b,k}^u} - \overline{X_{w,k}^u}) \cdot \overline{S_{w,k}^u} \cdot \widetilde{\alpha}_{1,k} \Big)$$

The racial gap among claimants might differ from the racial gap among unemployed due to three elements:

(i). $(\overline{X_b} - \overline{X_w}) \neq (\overline{X_b^u} - \overline{X_w^u})$, i.e. the racial gap in work history is different among claimants and among unemployed

(ii). $\sum_k \Big((\overline{S_{b,k}} - \overline{S_{w,k}}) \cdot (\overline{X_{b,k}} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) \Big) \neq \sum_k \Big((\overline{S_{b,k}^u} - \overline{S_{w,k}^u}) \cdot (\overline{X_{b,k}^u} \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}) \Big)$ i.e. the racial gap in state rule generosity is different among claimants and among unemployed

(iii). $\sum_k \Big((\overline{X_{b,k}} - \overline{X_{w,k}}) \cdot \overline{S_{w,k}} \cdot \widetilde{\alpha}_{1,k} \Big) \neq \sum_k \Big((\overline{X_{b,k}^u} - \overline{X_{w,k}^u}) \cdot \overline{S_{w,k}^u} \cdot \widetilde{\alpha}_{1,k} \Big)$ i.e. the racial gap in return on work history in the state is different among claimants and among unemployed

We focus on (ii) and (iii) as they matter for the size of the racial gap in UI explained by state differences—while (i) matters for the size of the gap explained by work history differences.

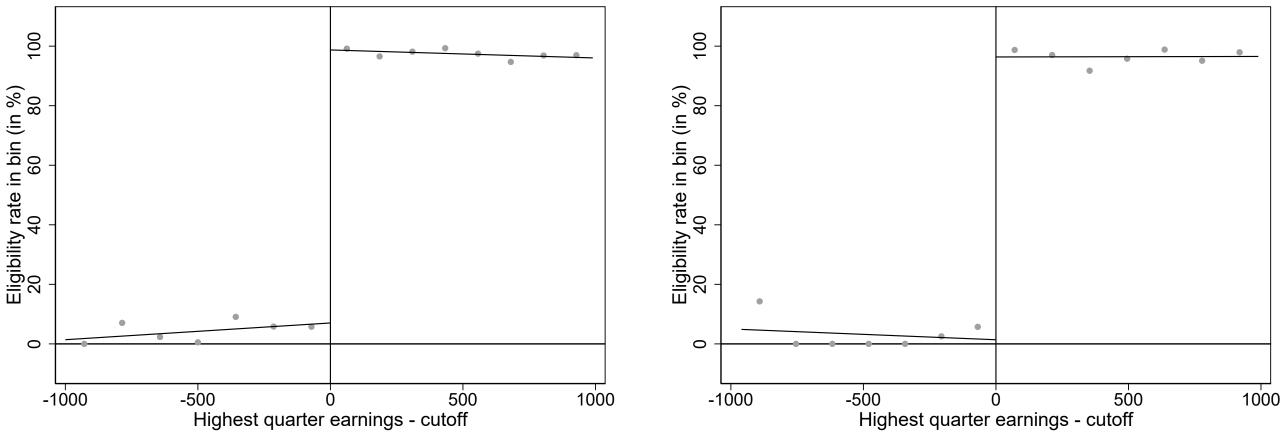
E.2 Density of claims around eligibility threshold

Do the precise UI rules affect differently the claiming decision of Black and White workers? To test this, we analyze the density of claims for Black and White workers, around a cutoff for monetary eligibility. This method presents the advantage that we do not need to have data on the population of unemployed to infer claiming behavior. Prior evidence suggests that unemployed workers are not responsive to precise eligibility rules: the density of claims around eligibility cutoff appears very smooth in Leung and O'Leary (2020). But for our purpose, it is important to test whether this is the case for both White and Black claimants separately. We hence analyze the density of claims for White and Black claimants separately

Figure E.1: Density of claimants around HQE eligibility cutoff

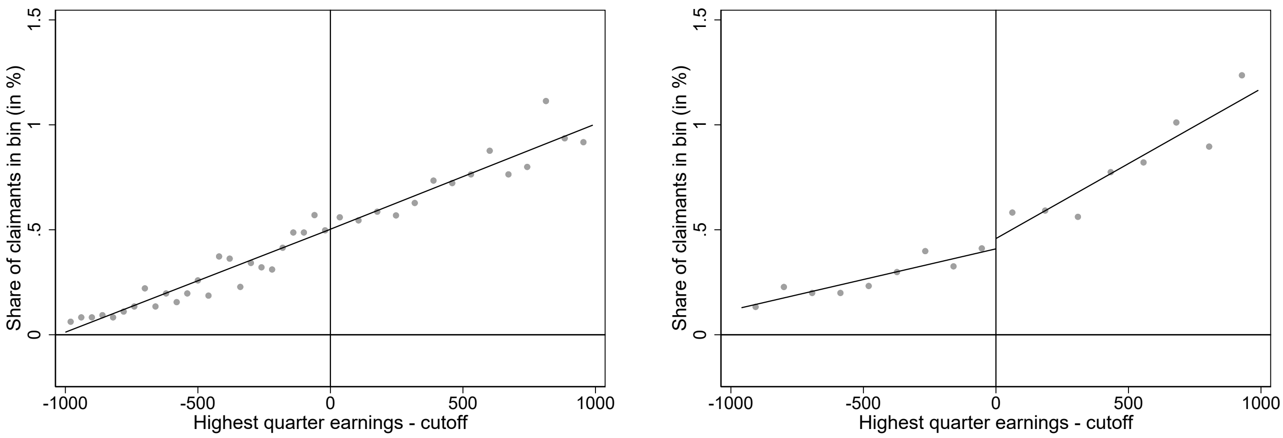
Eligibility rate around the HQE eligibility cutoff

(1) White claimants (2) Black claimants



Density around the HQE eligibility cutoff

(3) White claimants (4) Black claimants



Notes: This Figure shows the eligibility rate (in the upper part) and the density of claims (lower part) for claimants with highest quarter earnings at various distance to the minimum required highest quarter earnings in their state. The analysis is conducted on the restricted sample of claimants who satisfy the other monetary eligibility requirements, in 18 states where we could precisely measure the binding minimum required highest quarter earnings. To obtain these plots, we group Black and White claimants into \$10 bins of Highest Quarter earnings minus cutoff, and compute the eligibility rate and density in each bin. A regression discontinuity in these bins indicates that there is no significant jump in claimant's density around the HQE cutoff, neither for Black claimants (p-value of 0.160) nor for White claimants (p-value of 0.971). A fuzzy discontinuity analysis indicates that the probability of eligibility does not significantly affect the density of claim around the eligibility cutoff, neither for Black (p-value of 0.202) nor for White claimants (p-value of 0.711).

around the minimum of Highest Quarter Earnings required for eligibility in the state. We first restrict the sample of claimants to those who satisfy all eligibility criteria except for the minimum Highest Quarter earnings requirement. We group Black and White claimants into \$10 bins of Highest Quarter earnings minus cutoff, and compute the eligibility rate and density in each bin. In Figure E.1, we first present in Panels (1) and (2) the eligibility rate around the Highest Quarter earnings threshold for White and Black claimants: we see a clear jump at the threshold, with an eligibility rate close to 0% below the threshold, and close to 100 % above. In Panel (3) and (4), we present the density of claims around the threshold: we cannot detect any jump in the density of claims around the threshold. In a regression discontinuity, and find no significant jump in claimant's density around the HQE cutoff, neither for Black claimants (p-value of 0.160) nor for White claimants (p-value of 0.971). Using a fuzzy discontinuity, we also find that the probability of eligibility does not significantly affect the density of claim around the eligibility cutoff, neither for Black (p-value of 0.202) nor for White claimants (p-value of 0.711). Overall, this analysis suggests that Black and White workers are similar in their low responsiveness to precise eligibility rules. Therefore, there is no reason to expect that Black and White claimants with similar work history characteristics should react to the UI rules in their state differently.