Racial inequality in the U.S. unemployment insurance system

Daphné Skandalis*, Ioana Marinescu†, Maxim Massenkoff‡

July 4, 2022

Abstract

The U.S. unemployment insurance (UI) system operates as a federal-state partnership, where states have considerable autonomy to decide on specific UI rules. This has allowed for systematically stricter rules in states with a larger Black population. We study how these differences in state rules create a gap in the unemployment insurance that Black and White unemployed workers receive. Using administrative data from random audits on UI claims in all states, we first document a large racial gap in the UI that unemployed workers receive after filing a new claim. Black claimants receive an 18% lower replacement rate (i.e., benefits relative to prior wage, including denials) than White claimants. In principle, the replacement rate of each claimant mechanically depends on the rules prevailing in her state and on her work history (e.g., the earnings before job loss and the reason for separation from prior employer). Since we observe claimants' UI-relevant work history and state, we are in a unique position to identify the role of each factor. After accounting for Black-White differences in work history, differences in rules across states create a 8% Black-White gap in replacement rate (i.e., slightly less than half of the overall gap). Using a standard welfare calculation, we show that states with the largest shares of Black workers would gain the most from having more generous UI rules. Altogether, our results highlight that disparate state rules in the UI institution create racial inequality without maximizing overall welfare.

---

*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, Steven Durlauf, Eliza Forsythe, Nicole Fortin, Alix Gould-Werth, Peter Ganong, Nikolaj Harmon, Patrick Kline, Per Krusell, Camille Landais, Thomas le Barbanchon, Pauline Leung, Bruce Meyer, Robert Moffitt, Andreas Mueller, Suresh Naidu, Arash Nekoei, Matthew Notowidigdo, Laura Pilossoph, Evan Rose, Luke Shaefer, Benjamin Shoefer, 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, the University of Munich, the Zurich-Lausanne Workshop on "Job Search and the Labor Market", the Berkeley-Princeton Workshop on "Racial and Ethnic Disparities in the Economy".

†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 often have less access to these programs.[1] In particular, Black unemployed workers are less likely than White unemployed 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 (Ganong et al., 2021) and face more difficulties finding new jobs due to racial discrimination in hiring (Kline, Rose, and Walters, 2021). Various factors might create a gap in unemployment insurance between Black and White claimants. Factors outside of the UI system might play a role: 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 contribute to the gap: because UI rules are systematically less generous in 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.

Identifying the sources of the racial gap in UI presents two key data challenges: first, UI administrative data 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 us to construct a representative sample of all UI claimants for the entire U.S, from 2002 to 2017—the first to our knowledge. This is key for this paper, as it allows us to study both the racial gap in the unemployment insurance received by eligible claimants (i.e. the

[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.

intensive margin), and the gap in UI eligibility (i.e. the extensive margin). We confirm the validity of our data construction by comparing our data to aggregate statistics on new claims from the Department of Labor.

We start by presenting new descriptive statistics about unemployment insurance in the U.S. We document that states with a larger Black population have systematically stricter rules for unemployment insurance: the eligibility requirements are tougher, there is a lower cap on the weekly benefits eligible claimants can receive, etc. We then describe 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 substantial denial rate for new claims indicates that potential claimants face high uncertainty when deciding whether to claim. Most importantly, we find a significant 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 (i.e. unemployment benefits relative to prior earnings) when accounting for denials, while the equivalent replacement rate is 36% for White claimants: the replacement rate for Black claimants is 18% 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 differences. 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 benefit amounts, 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. For a small number of claimants, some of these variables are missing. We proxy these variables, using predictions based on claimants' other characteristics, such as age, gender, race, prior occupation, prior industry and prior wage, and show in robustness checks that our results are not sensitive to the use of proxies. We use a Oaxaca-Blinder style decomposition of the Black-White gap: we first estimate the state rule parameters by regressing UI outcomes on work history variables state by state in the sample of White claimants only, and then use these estimated parameters to compute each component of the racial gap.

Why do Black UI claimants receive an 18% lower replacement rate than White claimants? We find that racial differences in work history cause a 10% 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. Where is it coming from? Our decomposition shows that differences in state-specific rules cause Black claimants to have a 8% 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. This result suggests that the racial gap in UI is not 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 gap in eligibility (extensive margin) and in the replacement rate of eligible claimants (intensive margin). Black claimants are 19% less likely to be eligible. A 9% gap in eligibility is due to state-specific rules, while the rest of the gap 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. The UI system is progressive for eligible claimants: eligible claimants with higher prior earnings receive a lower replacement rate due to a cap on the weekly benefit amount. Since eligible Black claimants tend to have lower earnings, they should hence receive a higher replacement rate if it were not for differences in rules across states. In fact, differences in state rules generate a 3% 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 show that our finding of a 8% racial gap among claimants caused by state rule differences generalize to the *full population of unemployed workers*. We compare the population of unemployed workers in the Current Population Survey (CPS) and the population of claimants in our BAM administrative data. We find that the two population are similar in the dimensions that matter for the racial gap explained by state rule differences, in particular in the over-representation of Black people in stringent states. This suggests that unemployed workers don't select into claiming UI in a way that amplifies the role of state rule differences. To further quantify this, we simulate the racial gap in a scenario where all unemployed workers claim UI. We transform the population of BAM claimants to have the same work history and spatial allocation as the population of CPS unemployed workers, and decompose the racial gap in the simulated population. Our results indicate that state rule differences would cause a similar racial gap in UI in the full population of unemployed, as the one we estimated in the population of claimants.

After showing that state rule differences create racial inequality in UI, a key question is whether state rules are adapted to different economic conditions in the labor markets of different states. We lean on the literature on optimal unemployment insurance to measure the marginal welfare effect of an increase in unemployment insurance benefits *in each state* (Schmieder and von Wachter, 2016b). We find that the marginal social value of increasing the level of unemployment benefits is higher in states with a higher share of Black claimants, while the marginal cost is lower. Therefore, the marginal welfare is unambiguously higher in states with a higher share of Black claimants. These findings are robust to various calibration methods. In particular, as there is no separate estimate of the elasticity of unemployment duration with respect to benefits level for each state in the literature, we use a state-invariant estimate in our main calibration, reflecting the current state of knowledge. But we also estimate this elasticity in the BAM data and allow it to vary by state. We find that this elasticity decreases with the share of Black claimants in the state, such that our finding that the marginal welfare effects of UI increases with the share of Black claimants is strengthened when we use state-specific elasticity estimates. Overall, our welfare analysis indicates that the Black-White inequality in UI among workers with the same work history cannot be rationalized by differences across states in economic factors that are relevant for the design of unemployment insurance. Ostensibly race-neutral differences across states in unemployment insurance rules thus generate racial gaps that cannot be justified by the ultimate goals of unemployment insurance.

Finally, we expand the discussion on the role of state rule differences in racial inequality in UI, with three additional analyses. First, we analyze gaps in UI for claimants who differ in dimensions other than race. We show that, although we observe raw gaps for claimants from different genders, age groups or education levels, state rule differences do not play a role. The role of state rule differences appears specific to the racial gap. Second, we examine another potential source of racial inequality in the UI system: UI officers could be racially biased in the way they measure work history variables—even if they are not biased in the way they treat claimants given their measured work history. We compare the assessment of BAM auditors and that of UI officers, and find no evidence that UI officers are systematically biased against Black claimants. This confirms the idea that, in the context of unemployment insurance, racial inequality is built into the design of the institution, rather than produced by individual discriminatory behavior. Third, we offer a brief policy discussion, simulating the effect of various reforms aimed at reducing the racial inequality caused by differences in rules across states. We find that relaxing unemployment insurance eligibility requirements in the strictest states is a promising 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.

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 individuals' discriminating behavior. In the setting of unemployment insurance, institutional rules determine benefit calculation based on work history, which we can precisely measure. This allows us to show that the design of the

UI institution generates unequal insurance coverage for claimants with the same work history—without involving any discriminatory behavior by individuals. Historically, the economic literature might have underappreciated the role of institutions due to its focus on intentional discrimination by individuals (Small and Pager, 2020; Bohren, Hull, and Imas, 2022). We are contributing to a recent strand of empirical studies highlighting how the design of rules and institutions creates 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. While it is beyond the scope of our paper to analyze why 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)). Our main contribution to this literature is to explain why Black workers receive less UI than White workers in the U.S. The racial gap in UI recipiency had long been observed across survey data (e.g., Nichols and Simms (2012), Gould-Werth and Shaefer (2012), Kuka and Stuart (2021)).[4] However, the role of state rule differences has not been precisely quantified. Survey data, such as the Survey of Income and Program Participation (SIPP) analyzed by Kuka and Stuart (2021), do not allow to isolate the role of state rule differences as they do not contain information on who claimed UI, nor on the exact work history variables that are used by the UI administration. We discuss further the datasets on UI used in prior literature in section 3.3.

Third, our paper is related to welfare analyses of unemployment insurance. A rich literature offers a framework to determine which level of UI generosity can provide the maximum consumption smoothing at the lowest cost, depending on various measurable

[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. Rose (2021) shows that the ostensibly race-neutral rules for convicted offenders on probation generate racial disparities in incarceration.

[3] This hypothesis is consistent with research on racial diversity and punitiveness in criminal justice (Feigenberg and Miller, 2021), and on 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 Department of Labor data on the characteristics of UI recipients. Latimer (2003) uses unemployment insurance administrative data from West Virginia and document that Black workers are less likely to qualify for UI. Grant-Thomas (2011) provides suggestive evidence that Black workers are more likely to receive an improper denial for monetary reasons.

statistics (e.g., Baily (1978a), Chetty (2006),Schmieder and von Watcher (2016)). Using this framework, prior studies have measured how the welfare gains from UI extensions might change over the business cycle (Kroft and Notowidigdo (2016a), Schmieder, von Wachter, and Bender. (2012)). We present the first analysis of differences in the welfare effect of an increase in unemployment benefits across U.S. states, showing that the marginal welfare effect of additional unemployment benefits increases with the share of Black claimants in the state.

The paper is organized as follows. Section 2 presents the institutional context of unemployment insurance in the U.S. In Section 3, we present the BAM audit data. Section 4 describes our empirical strategy. Section 5 describes new descriptive statistics about UI claims. In section 6, we present our main finding of the racial gap in unemployment insurance explained by state rule differences. The welfare analysis in Section 7 aims to assess whether having stricter rules in states with a larger Black population is optimal. In section 9, we discuss various additional results. Section 9 concludes.

2 Institutional context

2.1 Unemployment insurance in the US

In the United States, workers who lose their jobs can receive weekly unemployment benefits after they file an initial claim, 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 Benefit Amounts are determined based on individual labor market characteristics and on UI rules, which vary across states. After the initial eligibility has been determined, claimants must keep filing continuing claims every one or two weeks.

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. These are relatively straightforward to verify through the state's quarterly wage records. The exact meaning of monetary eligibility depends on the state, but all states require sufficient Base Period Earnings. This is the sum of insured wages, i.e., wages subject to payroll taxes, in the last full four quarters at the date of application. Some states also consider Highest Quarter Earnings, the earnings received during the base period quarter with the most earnings. For instance, a 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, e.g., the weeks worked during the base period must exceed a certain threshold.

Second, claimants must also satisfy non-monetary criteria. The"separation eligibility" criteria require 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 separation 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. Additionally, the another type of non-monetary eligibility criteria requires that the claimant is able and available to work. In practice, this last criterion is mostly relevant for continuing claimants who may lose eligibility or receive a penalty if they earn too much income or do not search for work. It is less relevant for initial claims, which are the focus of this paper.

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 Benefit 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. 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 low in many states, and are binding for as many as one third of UI recipients. Therefore, these caps can considerably reduce the effective replacement rates, and are also an important source of progressivity within the UI system (among eligible claimants). As an example of how benefits vary with prior earnings, see the case of Florida in Appendix Figure C.4. 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 U.S. unemployment insurance system has been unique in its level of decentralization, operating as a federal-state partnership (Baicker, Goldin, and Katz, 2007). Within the federal guidelines, state legislatures can determine benefit amounts, duration, and eligibility requirements. In practice, 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. This fact was noticed when unemployment insurance was first established (Reticker, 1942).[5] Historians

[5]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).

have also argued that Democrats from Southern states imposed a decentralized system in 1935 to have the possibility to set a low level of generosity and avoid redistributing income towards their Black residents (Katznelson (2006)).

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). 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 random sampling procedure: they are selected randomly within each state, week, and claim type (the four types are: paid, monetary denials, separation denials, and other denials). Paid claims are sampled from all benefit payments applying to the audited week. Denied claims are sampled from the stock of claims that received a negative determination in that week. Information on the count of claims in the population, for each state, week, and claim type is recorded, such that the probability of being selected 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 collect complementary information through investigative processes when necessary: employer interviews, third-party verification, income verification, 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 full population of new applicants.[7] 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 omit these continuing claimants, restricting our sample to payments corresponding to

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

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

the first compensated week for paid claims, and denials of new 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 use weights equal to the inverse of the probability that a new claim is included in our sample. See Appendix A.1 for more details. 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 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 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 set of individual variables that are a priori not relevant for UI determinations, and are collected for statistical purposes[8]: 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 U.S. 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 Black claimants and Hispanics to non-Hispanic White claimants.

Claimants' work history Second, the BAM data contains the work history variables used 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 measured by the UI officer 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 as these were relevant for the initial benefit determination.

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

[8]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).

or non-monetary). In our main analysis, we analyze *all determinations* in the full sample of claims, and address missing work history variables by using proxies for work history variables (for more details, see Appendix A.3). In additional analyses, we keep only observations with non-missing work history variables by focusing on the racial gap in *monetary determinations*, using the sample of claimants that are either eligible or monetary-denied.

A small caveat when we focus on monetary determinations is that we do not observe the Highest Quarter Earnings for all claimants, because some states do not use this variable for their monetary determination during all the study period. The variable is missing for 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 that use the standard set of monetary variables, and for which we hence observe all relevant work history variables (i.e. Base Period Earnings, Highest Quarter Earnings and the ratio of the Highest Quarter Earnings over all Base Period Earnings).[9]

Unemployment insurance outcomes Finally, the BAM data contains information on two types of UI outcome: the eligibility status, and the Weekly Benefit Amount. 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, by taking the ratio of Weekly Benefit Amount over 40×Prior Hourly Wage, following the Department of Labor's definition.[10] In robustness checks, we also consider alternative measures: 52×Weekly Benefit Amount over Base Period Earnings or 13 ×Weekly Benefit Amount over Highest Quarter Earnings. In our empirical analysis, we implement the decomposition of the racial gap for various UI outcomes: we successively consider UI generosity for eligible and denied claimants together (coding benefits as 0 for those denied), the eligibility status (extensive margin) and weekly benefits for eligible only (intensive margin). 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 provided by the UI system.

3.3 Comparison with other data sources in the literature

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 U.S. states. While many papers discuss claiming behavior, data on UI claimants

[9]These 90% of states-months don't use Weeks Worked during the base period for their monetary determination, so we don't control for it when we analyze monetary determinations in this sample.

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

are scarce. To our knowledge, three other types of data sources can provide descriptive statistics on UI claimants, and each presents important limitations. First, the 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, e.g. 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 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. Tax data have been recently used to analyze UI receipt (Larrimore, Mortenson, and Splinter, 2022). Analyzing UI receipt among "likely eligible" unemployed workers allows to infer information on their claiming behavior (Blank and Card (1991), Anderson and Meyer (1997), Kuka and Stuart (2021)). It is however very sensitive to the definition of "likely eligible" unemployed workers. To determine which workers are "likely eligible", one needs to reconstruct the work history variables used by the UI administration. This can lead to important measurement error (Anderson and Meyer, 1997).

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 discuss the underlying identifying assumptions.

4.1 Decomposition of the racial gap in UI receipt

The determinants of UI According to UI rules, UI outcomes are a function of work history variables in each state. We consider the following model for UI outcomes:

$$Y_{i,k,g} = \alpha_{0,k} + X_i \cdot \alpha_{1,k} + \nu_{i,k,g} \tag{1}$$

where $Y_{i,k,g}$ represents the UI outcome for a claimant i in state k, race group $g \in \{b, w\}$ (Black or White). X_i denotes claimants' work history characteristics, and $\nu_{i,k,g}$ us an error term. The α coefficients represent the rules in the UI system: they might both change the impact of work history variable on outcomes ($\alpha_{1,k}$) and add a fixed term ($\alpha_{0,k}$). The UI rules are the same for everyone in each state. But in practice, UI outcomes could be affected by race, due to potential direct discrimination. Therefore we assume that UI outcomes are entirely determined by work history differences and state rules for White claimants, but not necessary for Black claimants. We hence assume $\mathbb{E}(\nu_k|X, D_g = w) = 0$, but allow for $\mathbb{E}(\nu_k|X, D_g = b) \neq 0$, where D_g indicates that claimants are in race group $g \in \{b, w\}$.

The components of the racial gap in UI Let's define the parameters of the average rule across states, weighted by the share of each state in the overall U.S. claimant population: $\overline{\alpha}_0 = \sum_k \frac{N_k}{N} \cdot \alpha_{0,k}$, and $\overline{\alpha}_1 = \sum_k \frac{N_k}{N} \cdot \alpha_{1,k}$, where N_k and N respectively denote the number of claimants living in state k and overall. Let's also define the coefficients $\widetilde{\alpha}_{0,k} = \alpha_0 - \overline{\alpha}_0$ and $\widetilde{\alpha}_{1,k} = \alpha_1 - \overline{\alpha}_1$. These coefficients 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. From equation 1, the components of the gap Δ in expected UI outcomes between Black and White claimants can measured in our study sample as follows (we provide details in Appendix B):

$$\hat{\Delta} = \hat{\overline{\alpha}}_1 \cdot (\overline{X_b} - \overline{X_w}) + \sum_k \left(\hat{\widetilde{\alpha}}_{1,k} \cdot (\overline{S_{k,b}} \cdot \overline{X_{k,b}} - \overline{S_{k,w}} \cdot \overline{X_{k,w}}) + \hat{\widetilde{\alpha}}_{0,k} \cdot (\overline{S_{k,b}} - \overline{S_{k,w}}) \right) + \hat{\nu}_b \quad (2)$$

where the hats denote that the coefficients are estimated (we explain the estimation procedure in Section 4.2). $\overline{X_g}$ denote the sample averages of work history variables for each race group. $\overline{S_{k,g}} = \frac{N_{k,g}}{N_g}$ represents the fraction of people from race group g living in state k (e.g. share of all Black UI claimants who live in Pennsylvania), where $N_{k,g}$ and N_g respectively denote the number of claimants in our sample from race group g living in state k and from race group g overall. $\overline{X_{k,g}}$ is the sample average of work history variables for people from race group g living in state k.

We can hence decompose the "raw" gap in the UI outcomes of Black and White claimants into three components. The first component is the gap *explained by differences in the work history variables* of Black and White claimants at the national level: $\hat{\overline{\alpha}}_1 \cdot (\overline{X_b} - \overline{X_w})$. 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 defined as the average of state rules. The second component is the gap *explained by differences in UI rules across states*: $\sum_k \left(\hat{\widetilde{\alpha}}_{1,k} \cdot (\overline{S_{k,b}} \cdot \overline{X_{k,b}} - \overline{S_{k,w} X_{k,w}}) + \hat{\widetilde{\alpha}}_{0,k} \cdot (\overline{S_{k,b}} - \overline{S_{k,w}}) \right)$. This gap would be eliminated if UI rules were the same across states. Finally, third component is the gap *unexplained by work history variables and state rules*: $\hat{\nu}_b$. 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 rule differences Differences in UI rules across states do not necessarily create a racial gap that disadvantages Black claimants. Under what conditions do we expect to find that 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 (2), as:

$$(\overline{S_{k,b}} - \overline{S_{k,w}}) \cdot (\overline{X_{k,b}} \cdot \hat{\tilde{\alpha}}_{1,k} + \hat{\tilde{\alpha}}_{0,k}) + (\overline{X_{k,b}} - \overline{X_{k,w}}) \cdot \overline{S_{k,w}} \cdot \hat{\tilde{\alpha}}_{1,k} \tag{3}$$

The differences in UI rules across states can influence the gap in unemployment insurance that we will estimate through two channels. First, Black claimants are disadvantaged when rules are stricter ($(\overline{X_{k,b}} \cdot \hat{\tilde{\alpha}}_{1,k} + \hat{\tilde{\alpha}}_{0,k})$ is negative) in states where Black claimants are over-represented ($(\overline{S_{k,b}} - \overline{S_{k,w}})$ is positive). Second, Black claimants are disadvantaged when the impact of work history characteristics is larger ($\hat{\tilde{\alpha}}_{1,k}$ is positive) in states where they have worse work history characteristics than White claimants ($(\overline{X_{k,b}} - \overline{X_{k,w}})$ is negative). In our descriptive analysis, we will provide 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

In this section, we first explain the general idea behind our estimation method for all UI outcomes, and then detail the specific approach for each of the UI outcomes considered.

The estimation method To estimate the components of the racial gap, we proceed in two steps. First, we estimate model 1. We hence measure the rule parameters $\hat{\alpha}_{0,k}$ and $\hat{\alpha}_{1,k}$, based on the observed relation between work history variables and the outcome state by state, in the subsample of White UI claimants only. This ensures that our estimates of the rule parameters cannot capture racial bias. We include all the work history variables that are used in the determination of the considered outcome in at least some states, from the following list: Base Period Earnings, Highest Quarter Earnings in base period, the ratio of the Highest Quarter Earnings to Base Period Earnings, Weeks Worked in base period, reason for separation. To allow for non-linear relations between work history variables and UI outcomes, we discretize continuous variables and interact monetary and separation variables. Second, following equation 2, we estimate the various components based on the estimates of the state rule parameters $\hat{\alpha}_{0,k}$ and $\hat{\alpha}_{1,k}$ and the various sample averages ($\overline{X_w}$, $\overline{X_{k,w}}$, $\overline{S_{k,w}}$, $\overline{X_b}$, $\overline{X_{k,b}}$, and $\overline{S_{k,b}}$). We obtain the unexplained gap by taking the difference between the gap in average UI outcomes, and the estimated gaps explained by work history and state rule differences. To account for the estimation of the rule parameters in the first step and for sample variation, we use bootstrap to compute standard errors of the estimated racial gap components.

Specific approach for each UI outcome In our empirical analysis, we first consider together 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. We now detail these two approaches. In our first approach, we include all determinations and use the full study sample. Our main estimates measure the gap in overall UI received by claimants. Then, we analyze racial differences in eligibility (extensive margin) and in UI generosity for eligible claimants (intensive margin). 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 variables otherwise. As some work history variables are missing for some claimants (see Section 3.2), we use different measures of work history variables in different samples, to always exploit the richest information available for all the sample considered. For the analysis of the gap among all claimants, we use proxies built from predicting work history variables based on claimants' prior wage, gender, age, occupation, industry, ethnicity and their interaction with race. For the analysis of the gap among eligible claimants, we use the actual Base Period Earnings variable, and we use a second type of proxies obtained from a richer set of variables to measure the other monetary variables. For more details, see Appendix A.3.

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 no other eligibility criteria.[11] Then, we analyze racial differences in monetary eligibility (extensive margin) and in UI generosity that monetary eligible claimants might receive if they also satisfy non-monetary eligibility criteria (intensive margin). 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 (Base Period Earnings, Highest Quarter Earnings, Ratio of Highest Quarter Earnings over Base Period Earnings).

Identification assumption As highlighted by Fortin, Lemieux, and Firpo (2011), while decomposition analyses are often treated as pure accounting exercises, correctly attributing

[11] 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 were 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.

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 rule differences to the racial gaps, if we do not omit relevant information that correlates with race when we estimate model (1). We might 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. To address these concerns, we implement a series of robustness checks. We start with testing the sensitivity of our results to our use of proxy for work history variables, in the analysis of the gap in all determinations. We focus on the analysis for which we observe all relevant work history variables: the analysis of the gap in monetary determination for the 90% of states-months that use the same set of monetary variables. We successively estimate the components of the racial gap using the actual work history variables, or the two types of proxies that we have constructed (see Appendix A.3). We show that our results remain stable whether we use the proxied or actual work history variables. Additionally, we re-estimate the state rule parameters in model (1) using various alternative methods. In particular, we estimate the state rule parameters using random forests to allow for more flexibility in the relation between UI outcomes and work history. We systematically find that our estimates of the components of the racial gap remain very close.

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)), 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 (Column (3)). Comparing columns (1) and (1) allows to determine which categories are over or under represented among claimants relative to the unemployed.

These statistics yield some novel findings. First, Black individuals represent 19% of all UI claimants, while White individuals represent 69% (column (1)). So Black and White claimants represent most of our sample, while other claimants are dispersed in various race categories. The proportion of Black individuals is lower among new eligible claimants and the proportion of White individuals is higher, indicating higher rejection rates for Black claimants (column (2)). Interestingly, the proportion of Black individuals 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 White individuals are slightly under-represented among claimants while Black individuals 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 White unemployed workers than for Black ones when we focus on the year 2005, as Gould-Werth and Shaefer (2012) did, instead of using data for the whole period 2002-2017.

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 earnings. As the UI system is progressive among eligible workers, this means that Black claimants receive a relatively higher replacement rate (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. 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 Black claimants, with an even larger gap in base period earnings. Black claimants also tend to have worked fewer weeks 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 Benefit 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. Note that this allocation of the Black population across U.S. states has been very persistent and precedes the introduction of the UI system in 1935 (see Figure C.1). The comparison of these maps indicates that there is a negative spatial correlation between the importance of the Black population and UI generosity, at least as far as the cap on WBA is concerned.

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 summarize all dimensions of UI generosity into one index, by taking the statutory Weekly Benefit 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: $\overline{X} \cdot \hat{\alpha}_{1,k} + \hat{\alpha}_{0,k}$. Panel (1) 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 (2) 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 (3) shows that the formula replacement rate (weekly benefits over weekly base period earnings), falls by 0.4 percentage points with every 10 percentage point increase in share Black. In Panel (4), we analyze how frequently states grant eligibility to claimants who quit their prior job. 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.2 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 2. The conclusions remain the same.

State rule 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.3. First, we measure the work history premium by taking an index, corresponding to the premium on her Weekly Benefit Amount that a claimant with average work history characteristics should receive in that state: $\overline{X} \cdot \hat{\alpha}_{1,k}$ (notations explained in Section 4.1). Second, we 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. We also use an index summarizing all the work history characteristics relevant for UI, corresponding to the Weekly Benefit Amount that a claimant with these specific work history characteristics should receive given the average UI rules across states: $X_i \cdot \hat{\overline{\alpha}}_1$. Overall, it appears from all panels in Figure C.3 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

In this section, we decompose the racial gap in UI among claimants. The objective is to quantify the role of disparate state rules in creating racial inequality among claimants.

6.1 The overall racial gap in UI

We present our main results in Table 3. Each column corresponds to a UI outcome. The top panel presents the raw Black-White gap in these outcomes, followed by a decomposition 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 bottom panel of the table reports the gaps as a percent of the White mean for that outcome.

The raw Black-White gap On average, Black claimants receive a $92 lower Weekly Benefit Amount (WBA) than White claimants (Table 3, first line in column (1)). This is 34% less than the average for White claimants (column (1), bottom panel). In column (2), we analyze the difference in replacement rates, which provides a better measure of how UI insures against income loss. The first line in column (2) shows that replacement rates for Black claimants are 7 percentage points lower, corresponding to a 18% gap relative to White claimants (column (2), bottom panel). The gap in replacement rates is smaller than the gap in WBA, since Black claimants tend to have lower prior earnings (see the Table 2). Still, the 18% gap in replacement rate implies substantially less insurance against job loss compared to White claimants. The overall Black-White gap in unemployment insurance receipt among claimants reflects a gap in eligibility—the extensive margin—and a gap in benefit amounts among eligible claimants—the intensive margin. We analyze these outcomes in columns (3)-(5). Black claimants are 14 percentage points less likely to be found eligible, which corresponds to a 19% gap relative to White claimants (column (3), first line, and second line in the bottom panel). When they are eligible, Black claimants receive $66 less in benefits, which represents a 18% gap (column (4), first line, and second line in the bottom panel). Perhaps surprisingly, Black claimants' replacement rate conditional on being eligible is not significantly different from that of White claimants (column (5)). 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 their three components. We first report the gap explained by state rule differences: the component (i) is reported in levels in the top panel and as a share of the White mean in the bottom panel. The estimates imply that, due only to state rules, Black claimants receive $31 or 11% less in benefits (column (1)) and an 8% (or 3 percentage point) lower replacement rate than White claimants (column (2)). We then estimate the effect of state rule differences on the extensive and the intensive margin of UI. State rule differences cause a 9% Black-White gap in the eligibility rate (column (3)), implying Black claimants are more likely to be denied benefits due to the stricter rules in their state. Moreover, even when they are eligible, Black claimants are disadvantaged by state rules. Columns (4) and (5) show that differences in state rules cause a 4% gap in the Weekly Benefit Amount, and a 3% gap in the replacement rate among those receiving benefits. These results indicate that state rules contribute to a racial group through both the extensive and the intensive margin of UI. These estimates of the gaps explained by state rule differences carry our key findings. Black claimants receive a 8% 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 comparison between the 18% raw gap in replacement rate (line 1, column (2)) and the 8% gap caused by state rules in (line 2, column (2)) suggests that roughly half of the raw gap in replacement rate is due to institutional factors.

The gap explained by work history We next report the gap explained by work history differences: this component (ii) is reported in levels in the top panel and as a share of the White mean in the bottom panel. Due to different work history, Black workers get 24% ($65) lower weekly benefits than White workers (column (1)). The gap in replacement rates explained by work history is relatively smaller than the gap in raw benefit levels explained by work history: 10% (4 percentage points; column (2)). This is because work history variables mainly include measures of prior earnings, and Black claimants' lower prior earnings disadvantage them in terms of eligibility but advantage them in terms of replacement rate conditional on eligibility. This can be seen in columns (3) and (5). Column (3) shows that racial differences in work history make Black claimants 12% less likely to be eligible than White claimants. However, eligible White claimants' higher prior earnings are mechanically associated with a lower replacement rate due to the cap on WBA. Thus, column (5) shows that work history differences increase the replacement rate among eligible Black claimants by 2 percentage points, or 4% relative to the White mean. For eligible Black claimants, the negative effect of state rules (3% in favor of White claimants) is compensated by the positive effect of work history (4% in favor of Black claimants; see column (5)). Overall, this leads to an insignificant racial difference in replacement rates for eligible claimants (first line in column (5)). Note that this is merely accidental: work history differences do not necessarily have to compensate for inequalities introduced by state rules.

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, column (1)), and monetary determinations are the type of decisions that the literature typically focuses on (Leung and O'Leary (2020), Souza and Luduvice (2020), Chao (2022)). Moreover, for monetary determinations, we do not need to use any proxy work history variables, because 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 columns (1)-(2) shows that that Black claimants are disadvantaged in monetary determinations, like they are overall (consistent with Table 2). In monetary determinations, Black claimants get \$76 lower weekly benefits (25%), and 3 percentage point lower replacement rate (8%) than White claimants (Black-White gaps in columns (1)-(2)).

Importantly, we see that state rule differences play an important role. They generate a 1.6 percentage point lower replacement rate, with represents a 3.8% gap (Component (i), column (2)). At the extensive margin, state rule differences are responsible for a 2 percentage points lower monetary eligibility rate for Black claimants, which amounts to a 2% gap (Component (i), columns (3)). As we saw that they are responsible for a 7 percentage points lower eligibility rate overall (Table 3), this indicates that state rules also create a substantial gap in separation eligibility. This is consistent with the large negative correlation between the proportion of Black claimants in a state and the frequency of exceptions to the no-quit rule in Figure 2. At the intensive margin, the gaps in the amount of UI received conditional on being eligible are almost identical to the gaps in overall eligibility (columns (4) and (5)).

Overall, the components of the racial gaps in monetary determinations are qualitatively similar to those in all determinations (Table 3): differences in state rules generate a significant racial gap for all outcomes; 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. Differences in state rules generate substantial gaps between Black and White claimants with similar work history in the outcomes from monetary determinations alone. These results reinforce the conclusion from our analysis of all determinations.

6.3 Robustness checks

We first test the sensitivity of our analysis of the gap in UI generosity to our use of proxies for work history variables in Table 3. As explained in Section 4.2, we use proxies in our analysis of all determinations as the relevant work history variables are missing for some claimants. To test how this might affect our results, we focus on the analysis of monetary determinations, for which we observe all the relevant work history variables. We re-estimate the various determinants of the racial gap in the outcome of monetary determinations, using either proxies (like in Table 3) or the actual work history variables (like in Table 4). Results are shown in Table C.2: our estimates remain very similar to the main results.

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 C.3: our estimates are unaffected by the inclusion of these controls.

Next, we re-estimate the state rule parameters using machine learning. Our main analysis uses linear regression to uncover how work history maps to benefit levels in each state. Machine learning models may better capture the non-linearities inherent in all state determinations. For all states, we fit a Random Forests model that predicts each UI outcome based on the relevant work history variables. The models are fit using only White claimants, just as in the main analysis. In order to have a larger sample size for cross-validation, we expand our sample of new claimants, adding paid claimants audited later in their spells. Using a Random Forest method also gives us the flexibility to add year fixed effects, and allow have rules vary over time. The Random Forest hyper-parameters for each state are selected using a random grid search and 5-fold cross-validation. In general, the Random Forests predictions fit both White and Black claimants better than the linear regressions. We present in Table C.4 the estimated components of the racial gap using the predictions from the Random Forests model. The estimates align closely with the results in Table 3.

6.4 Racial gaps caused by state rules for *all* unemployed workers

We have shown how state rule differences affect the racial gap in UI received by UI claimants. Here, we extend our analysis to all unemployed workers, including those who don't claim UI: we assess how much gap in UI would be explained by state rules, if all unemployed workers claimed. This is a useful benchmark, as one might consider that the the UI system would be effectively race-neutral if Black and White claimants with the same work history could receive the same benefits *if they claimed.*

For anyone who claims UI, the process determining UI outcomes based on state, work history, and potentially race, is the same as the one described in model 1. We can hence estimate the components of the racial gap among all unemployed, from some key state-level statistics for the unemployed population, just like for claimants (we provide the formula in Appendix D). Comparing the formulas of the gap in the two populations, one can see that the racial gap explained by state differences among claimants could differ from that among unemployed for two reasons. First, it would differ if the correlations between state rule generosity and the share of each racial group living in the state are different in the population of unemployed workers and in the population of claimants. Second, it would differ 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.

To assess whether the correlations are different, we compare the population of newly unemployed workers from the monthly Current Population Survey (CPS) to the new claimants in our BAM study dataset. In the CPS, we measure the size of the population and the average wage in the last occupation for Black and White newly unemployed workers in each state. In Figure C.5, 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 item listed above. We see that Black people are over-represented in stringent UI states, both among claimants and among all unemployed. In other words, Black claimants are over-represented in stringent states not because they claim more in those states, but because this is where Black unemployed workers live. 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 item listed above. Similarly, we see that the prior wage of Black people tends to be less far below that of White people in states with a lower premium on work history, both among claimants and among all unemployed.

Overall, the statistics presented in Figure C.5 suggest that the racial gap explained by state rule differences among unemployed workers is similar to the one we estimated among claimants. To test that more directly, we quantify the size of the racial gap explained by state rule differences among unemployed workers that is implied by these statistics. We simulate the unemployed population: we modify the sample of BAM claimants by calibrating the share of population and the average base period earnings in each race group and each state relative to the population average to match the corresponding statistics for the CPS unemployed (i.e. the statistics presented in Figure C.5). We then apply our decomposition method to this simulated population of unemployed, to measure the components of the racial gap. The results are presented in Table C.5. The estimate of the racial gap in replacement rate caused by state rule differences in the full population of unemployed is similar to our estimate for the population of claimants (comparing columns (4) and (6) to column (2)). In sum, our comparison between the population of claimants and of unemployed workers suggest that the gap explained by state rule differences would be similar in the two populations.

7 Welfare analysis

Can the differences in UI generosity across states be justified by differences in economic conditions? To address this question, we examine how far each state is from providing the level of benefits that would be optimal given the local economic conditions. Following the standard approach in the literature (Schmieder and von Wachter, 2016a), we measure the marginal welfare effect of increasing UI in each state. Prior studies have measured the changes in the welfare effects of UI extensions over the business cycle (Kroft and Notowidigdo (2016a), Schmieder, von Wachter, and Bender. (2012)), but there exists no analysis to our knowledge of the differences across states in the welfare effect of increasing unemployment benefits.

7.1 Marginal welfare effect of a UI increase, state by state

Can differences in economic conditions across states justify the differences in UI rules that generate a racial gap in UI? Maybe in states with a large Black population, local economic conditions make it desirable for workers to have relatively low unemployment insurance and relatively low taxes, so that their current UI rules are optimal. Alternatively, maybe workers would benefit from having relatively generous UI benefits and relatively high UI taxes in these states, implying that their current UI rules are suboptimal. To address this question, we need to consider all the differences in economic conditions across states that are relevant for unemployment insurance. We lean on the literature on optimal unemployment insurance, which provides a formal framework to determine which economic factors should be relevant (Baily, 1978b; Chetty, 2006). We use the formula provided by Schmieder and von Wachter (2016a) to measure, for each state, the overall welfare effect from increasing the transfers to the unemployed by $1 (see Appendix E.1 for more details). The marginal welfare effect corresponds to the social value from increasing UI (from consumption smoothing) minus its behavioral costs (from increased unemployment). In this framework, assessing the marginal welfare effect of a UI increase in each state requires a measure for each state of the exit rate out of unemployment, the fraction of workers staying unemployed at least until the end of the maximum duration of benefits, the amount of taxes collected and of benefits distributed, the average earnings of employed workers and of workers who have been unemployed for less than the maximum duration of benefits, and the elasticity of unemployment duration with respect to UI benefits.

7.2 Calibration

To measure the marginal welfare effect, we first assemble from various data sources the statistics related to state-level unemployment, UI benefits and taxes (see Appendix E.2 for more details). We approximate the marginal social value from consumption smoothing using the difference in income between the employed and the UI recipients multiplied by the coefficient of risk aversion (Baily, 1978b; Gruber, 1997; Chetty, 2006; Kroft and Notowidigdo, 2016b; Leung and O'Leary, 2020). We use the standard value 2 for the coefficient of risk aversion in our main calibration, and show that our conclusions remain unchanged for alternative values. We note that using the drop in income associated with unemployment, rather than the drop in consumption might lead us to overestimate the social value. We therefore abstain from interpreting the magnitude of the welfare effects of benefits increases. However, we can interpret the cross-state correlation between marginal welfare effects and the share of Black claimants, to the extent that differences between the drop in incomes and the drop in consumption levels are similar across states. Since the consumption of Black workers drops *more* than that of White workers facing a similar income shocks (Ganong et al., 2021), the drop of consumption (and hence the social value of UI) should *be even larger* in states with a higher share of Black population than what our estimates suggest.

Empirical assessments of the welfare effects of UI typically focus on the measure of the elasticity of unemployment duration with respect to UI benefits. While there are many estimates for this elasticity for the U.S., there are no systematic state-level estimates. Therefore, we first use for our main calibration the value 0.38, i.e. the median of the elasticity estimates in the literature (Schmieder and von Wachter, 2016a), and show that our conclusions remain unchanged for alternative values. Although assuming that the duration elasticity is the same across states might miss important aspects of this welfare calculation, it is a useful benchmark, as it reflects the current state of knowledge. Second, we test empirically whether the elasticity changes with the state-level share of Black claimants. The BAM data are ideally suited to estimate the effect of UI across states, since it is one of the rare datasets covering all U.S. states with detailed information on UI and for large samples of workers. In Table C.6, we find that the elasticity of benefit duration with respect to the replacement rate decreases with the share of Black claimants in the state. This implies that the marginal welfare costs due to behavioral effects are even lower in states with a high share of Black claimants.

7.3 Marginal welfare effects of UI and the share of Black claimants

We present the state-level correlation between the share of Black claimants and the marginal social value (consumption smoothing) of a \$1 increase in benefits, the marginal behavioral costs, and the marginal overall welfare effects in Figure 3. In Panel (1), we see clearly that the marginal social value increases with the share of Black claimants in the state. This is because the drop in income associated with unemployment is larger in states with a large Black population. Conversely, Panel (2) shows that the marginal cost decreases with the share of Black claimants. This is in part explained by the fact that more workers stay unemployed *after* the maximum benefit duration in these states. Therefore, even if more generous unemployment insurance tends to lengthen their unemployment duration, it has limited consequences on the duration of *paid* unemployment benefits. The result presented in Panel (2) is using our conservative assumption that the elasticity of unemployment duration with respect to benefits level is constant across states. Using instead the state-specific estimates obtained in Table C.6 would further accentuate the negative correlation. Finally, Panel (3) shows a positive correlation between the share of Black claimants and the overall marginal effect (i.e. marginal social value minus marginal behavioral cost). Importantly, this does not depend on the relative magnitude of the social value and of the behavioral cost, given that both contribute to increase the marginal welfare effects for states with more Black claimants. Therefore, the positive correlation between the marginal welfare effect of a UI increase and the share of Black claimants is not sensitive to the value of specific parameters. Appendix Figure C.6 confirms that this result holds with alternative parameter values for the elasticity of unemployment duration with respect to benefits, or for risk aversion. Overall, this analysis shows that having less generous unemployment benefits in states with a higher share of Black claimants is not socially optimal. Racial inequality caused by differences in rules across states in the unemployment insurance system cannot be justified as welfare maximizing.

8 Additional results

8.1 Do state rule differences cause gaps, beyond the racial gap?

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 groups. In Figure C.7, we present graphically the different components of the gaps in Weekly Benefit 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 with more or less than some college education. We present both the overall gap (full bar), and the gap explained by state rule differences (dark blue part of bar). Overall, women, younger and more educated claimants also tend to receive a lower replacement rate than men, older claimants, and less educated claimants respectively. But interestingly, there is virtually no gender gap nor age or education gap explained by differences in state rules. Additionally, we present the Black-White gap in UI outcomes for claimants in different gender, age and education groups in Figure C.8: Black claimants are similarly disadvantaged across all demographic groups. Overall, these results support our focus on the consequences of the UI system for racial inequality. Although it is beyond the scope of our paper to test this causal link, we note that these results are consistent with the idea that Southern states may have persistently had stricter rules *because of* their large Black population.

8.2 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 Black claimants can be seen as evidence of racial bias. We analyze mistakes detected by BAM auditors in UI outcomes. 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 claimant characteristics.[12] We present the results in Table C.7. In column (1), we see that the size of mistakes in the assessment of the Weekly Benefit Amount is not significantly different for Black and White claimants. In column (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 column (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 the replacement rate: Black claimants appear to receive a 0.7 percentage point lower replacement rate due to differential mistakes in replacement rate (column (4)). But this correlation becomes small and sometimes insignificant when we control for other claimants' characteristics (column (5) and (6)). Overall, Table C.7 suggests 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. 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. 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.

8.3 Policy simulations

The racial gap generated by state rule differences would mechanically disappear if all states had the same UI rules. But how would the racial gap change if only one aspect of state rules was harmonized? In this section, we discuss how racial inequality can be decreased by

[12] These correlations cannot be interpreted causally, as claims might have unobserved characteristics that expose them differentially 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.

partially harmonizing the UI system across states.[13] Indirectly, this analysis helps highlight which dimension of the current system contributes the most to the existing racial inequality.

We present the results in Figure 4: 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. The dark blue bar is the gap explained by state rules in the alternative, and the light blue part of the bar is the gap explained by other components. We successively set the federal minimum at various quartiles of the distribution of the parameter in our study period across states, up to the maximum so that 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.[14] We successively consider two types of partial reforms: first, the harmonization of policy parameters related to benefits generosity for those who are eligible, second, the harmonization of policy parameters related to 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).

Harmonizing benefits levels We first consider reforms to the benefit calculations. 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). However, 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, column (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.

Harmonizing eligibility criteria Let's now consider the reforms of the eligibility criteria. In Figure 4 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 $2,964

[13]Many arguments have been brought to 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).

[14]We discuss evidence suggesting it might be a reasonable assumption in Section 6.4.

of earnings during the base period, which would only affect a fourth of states) would decrease the gap induced by state rule differences from 8.4% (Table 3, column (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 $1,500 during the base period, which lies between the median and the third quartile.[15] In Panel (4), we harmonize the requirements for separation eligibility.[16] When we align the treatment of quitters to the most generous state, the gap explained by state rule differences is reduced to 6.2%, and the overall gap is reduced to 14.4%.

Racial gaps, across the prior wage distribution Our results in Figure 4 indicate that harmonizing eligibility requirements does not only reduce the gap explained by state rule differences, but also the gap explained by work history differences. Intuitively, this is because it increases UI generosity towards claimants with lower prior earnings. This is illustrated in Figure C.9: we present the gap in the average replacement rate for claimants at different quintiles of the distribution of prior hourly wages, under each policy reform, assuming full harmonization across states to the level of the most generous state. We also present the effect of partial reforms on the racial gap across prior wage quintiles in Figure C.10, and the effect of the full harmonization reforms on the racial gap for different demographic group in Figure C.11. Harmonizing the cap on WBA decreases the racial gap explained by state rule differences, but only for the two highest prior wage quintiles. In contrast, harmonizing eligibility requirements reduces the racial gap primarily at the bottom of the prior wage distribution.

Overall, our analysis shows that, among the partial federalization reforms we consider, imposing a federal maximum for earnings eligibility requirements is the best way to decrease racial inequality, and make the UI system more progressive. 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).[17]

9 Conclusion

In this paper, we analyze a novel representative sample of new UI claimants obtained from random audits of UI claims. We first document a raw 18% Black-White gap in the UI

[15]More specifically, Dube (2021) recommends setting the requirement to $1,000 during the highest quarter, and $500 in a second quarter during the base period.

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

[17]We also present in Figure C.12 a measure of the direct cost (i.e. without accounting for the behavioral response) associated with each of the policy reforms considered: the average Weekly Benefit Amount per claimant. Fully harmonizing the cap on WBA is the most expensive policy: the average WBA per claimant reaches $294 (panel 1), which is 19% more than the actual average of $248. In contrast, harmonizing earnings eligibility criteria increases the cost to $263 or a 6% increase (panel 3).

received by claimants: Black claimants receive a 29% replacement rate vs. 36% for White claimants. Using a Oaxaca-Blinder style decomposition, we show that differences in state UI rules cause an 8% Black-White gap in the replacement rate. We further show that state differences would create a similar gap among all Black and White unemployed workers with the same work history, if all unemployed workers were to claim unemployment benefits. We then examine if the differences in rules across states appear to respond to differences in economic conditions. Using a standard welfare analysis, we show that it is not the case: the marginal welfare benefit of providing higher unemployment benefits is *higher* in states with a higher share of Black claimants. Going towards more harmonized UI rules across states could hence ensure that Black and White claimants with the same work history receive more similar insurance against job loss, and would also increase overall welfare.

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 more difficulties finding a new job due to racial discrimination in hiring (Kline, Rose, and Walters, 2021). Receiving lower unemployment insurance might also induce Black workers 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 shows that people tend to dislike re-distributive policies when they disproportionately benefit other racial groups (e.g., Alesina, Glaeser, and Sacerdote, 2001). This suggests 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. URL `https://www.jstor.org/stable/2586963`. Publisher: Oxford University Press.

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. URL `https://www.nber.org/papers/w29245`.

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. URL `https://www.nber.org/papers/w8524`.

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.

Baily, Martin. 1978a. "Some Aspects of Optimal Unemployment Insurance." *Journal of Public Economics* 10 (3):379–402.

———. 1978b. "Some Aspects of Optimal Unemployment Insurance." *Journal of Public Economics* 10 (3):379–402.

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 FranÃ§ois Fontaine. 2021. "Unemployment Duration and the Take-Up of Unemployment Insurance." URL https://www.ssrn.com/abstract=3767275.

Bohren, J. Aislinn, Peter Hull, and Alex Imas. 2022. "Systemic Discrimination: Theory and Measurement." URL https://www.nber.org/papers/w29820.

Chao, Ying. 2022. "A Quantitative Analysis of Relaxing UI Eligibility Requirements: Evidence from the Pandemic Unemployment Assistance." URL https://drive.google.com/file/d/1Ni_DsowiBwX2kUVbTvE8t_Tg-g-Pux5C/view?usp=sharing&usp=embed_facebook.

Chetty, Raj. 2006. "A General Formula for the Optimal Level of Social Insurance." *Journal of Public Economics* 90(10-11):1879–1901.

Derenoncourt, Ellora and Claire Montialoux. 2021. "Minimum Wages and Racial Inequality*." *The Quarterly Journal of Economics* 136 (1):169–228. URL https://doi.org/10.1093/qje/qjaa031.

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

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, FranÃ§ois and Andreas Kettemann. 2019. "Quasi-experimental Evidence on Take-up and the Value of Unemployment Insurance,." URL https://www.dropbox.com/s/scx481dm0y2fepi/Fontaine_Ketteman_last_version.pdf?dl=0.

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. URL https://press.uchicago.edu/ucp/books/book/chicago/W/bo3633527.html.

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.

Gruber, Jonathan. 1997. “The Consumption Smoothing Benefits of Unemployment Insurance.” *The American Economic Review* 87 (1):192–205. URL https://www.jstor.org/stable/2950862. Publisher: American Economic Association.

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.

Kroft, Kory and Matthew J. Notowidigdo. 2016a. “Should Unemployment Insurance Vary with the Unemployment Rate? Theory and Evidence.” *The Review of Economic Studies* .

———. 2016b. “Should Unemployment Insurance Vary with the Unemployment Rate? Theory and Evidence.” *The Review of Economic Studies* .

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.

Larrimore, Jeff, Jacob Mortenson, and David Splinter. 2022. "Earnings Shocks and Stabilization During COVID-19." *Journal of Public Economics* :104597.

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. URL `https://www.aeaweb.org/articles?id=10.1257/pol.20170262`.

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.

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 BlackâWhite child poverty gap in the United States." *Socio-Economic Review* 19 (3):1005–1035. URL `https://doi.org/10.1093/ser/mwz025`.

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). URL `https://academic.oup.com/qje/article/136/2/1199/6039346?login=true`.

Schmieder, Johannes F. and Till von Wachter. 2016a. *Annual Review of Economics* .

———. 2016b. "The Effects of Unemployment Insurance Benefits: New Evidence and Interpretation." *Annual Review of Economics* 8 (1):547–581. URL https://doi.org/10.1146/annurev-economics-080614-115758.

Schmieder, Johannes F., Till von Wachter, and Stefan Bender. 2012. "The effects of extended unemployment insurance over the business cycle: evidence from regression discontinuity estimates over 20 years." *The Quarterly Journal of Economics* .

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.

Souza, Gustavo de and AndrÃ© Victor Luduvice. 2020. "Optimal Unemployment Insurance Requirements." URL https://drive.google.com/file/d/1tLeBEhjUVLrtr3y44xHPCO2Xf8Ilo2pN/view?usp=sharing&usp=embed_facebook.

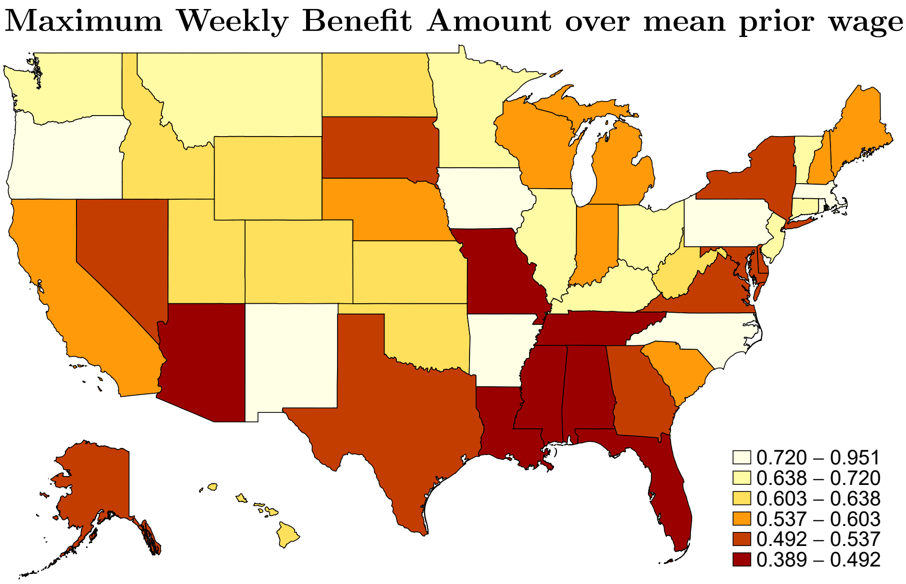
USDOL. 2019. "Department of Labor Handbook on UI eligibility." https://oui.doleta.gov/unemploy/pdf/uilawcompar/2019/monetary.pdf.

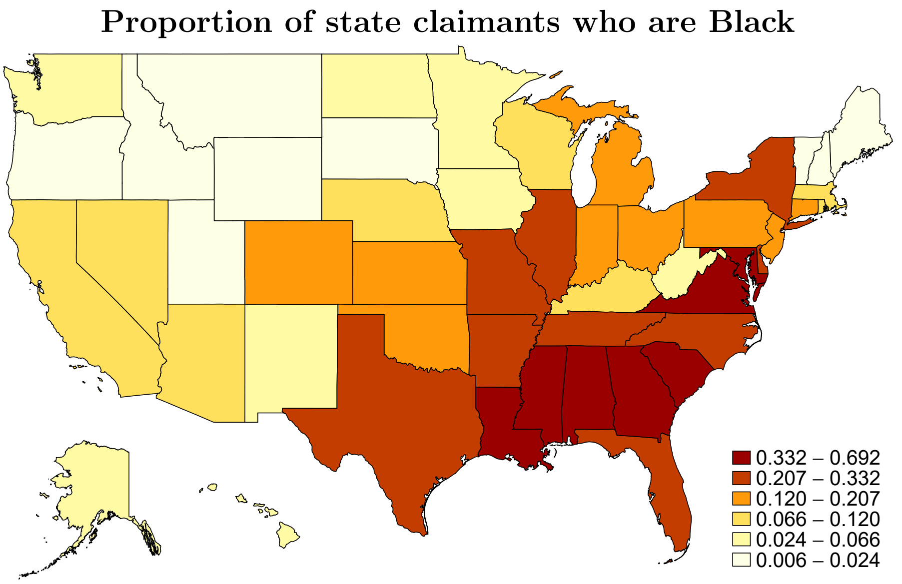
Woodbury, Stephen A. 2002. "Unemployment insurance overpayments and underpayments." .

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

10 Tables and Figures

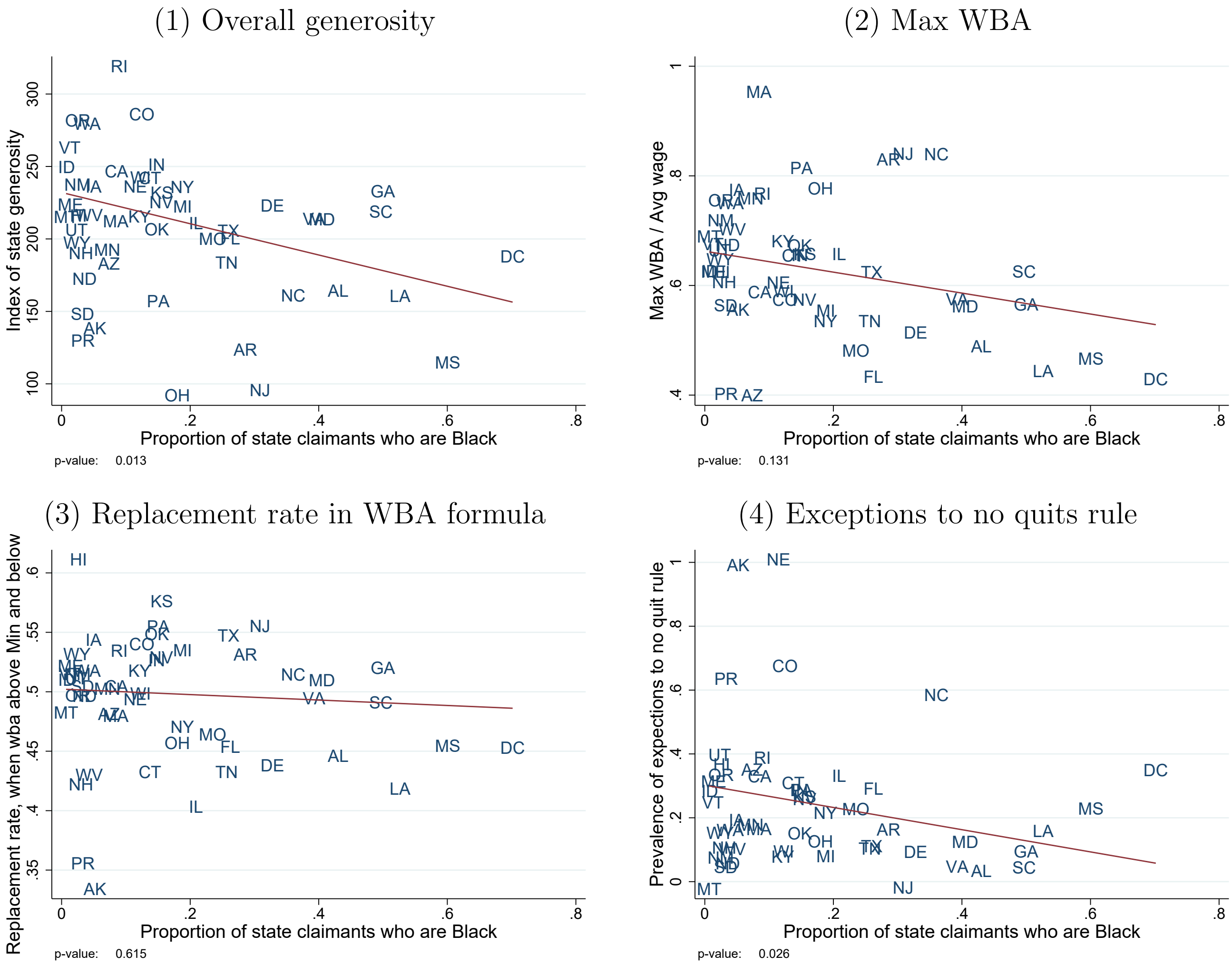
Figure 1: Maximum Weekly Benefit Amount and share of Black claimants





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 Benefit Amount according to the rule in each U.S. 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.

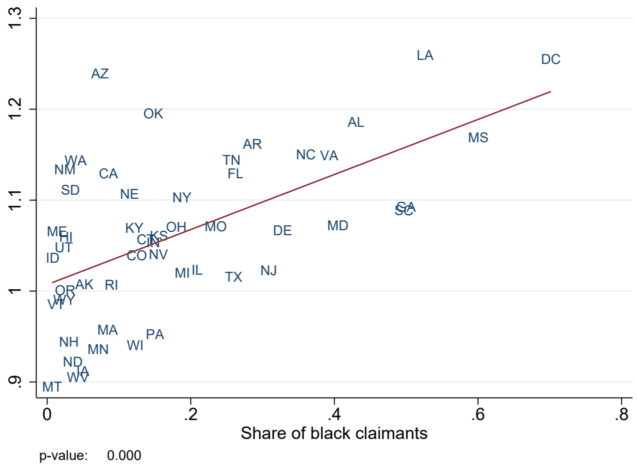
Figure 2: State rules and racial composition



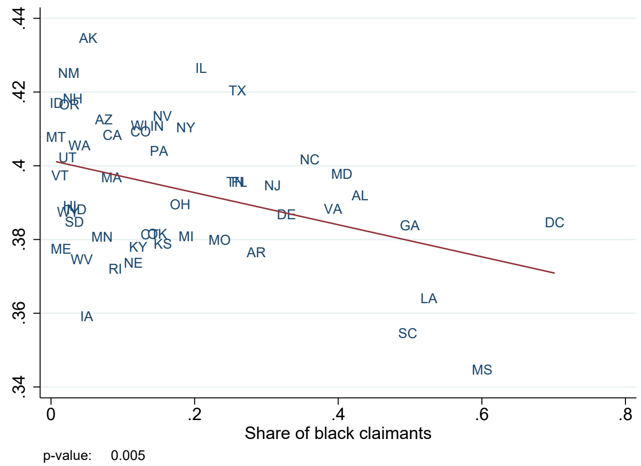
Note: This Figure presents the correlation of state rule generosity and the share of claimants in the state who is Black. We measure state generosity using an index summarize all dimensions of state rules in Panel (1) (see Section 5.3) ; the statutory maximum level of weekly benefits in Panel (2) ; the 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 (3) ; the proportion of claimants quitting their jobs who are eligible in Panel (4). 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: Correlation between the marginal welfare effects of UI benefits and the share of Black claimants

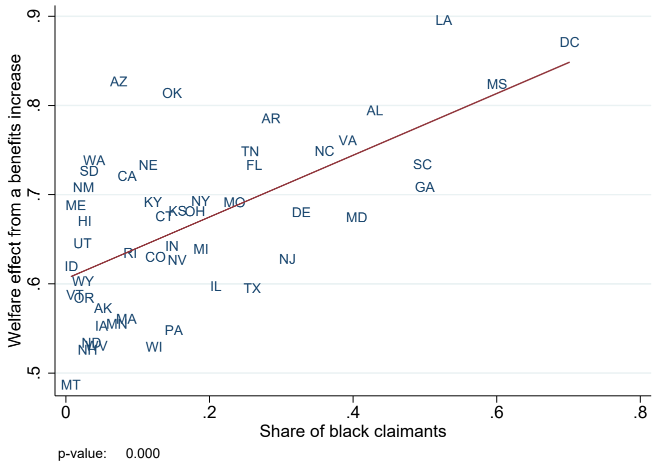
(1) **Social value**



(2) **Behavioral cost**

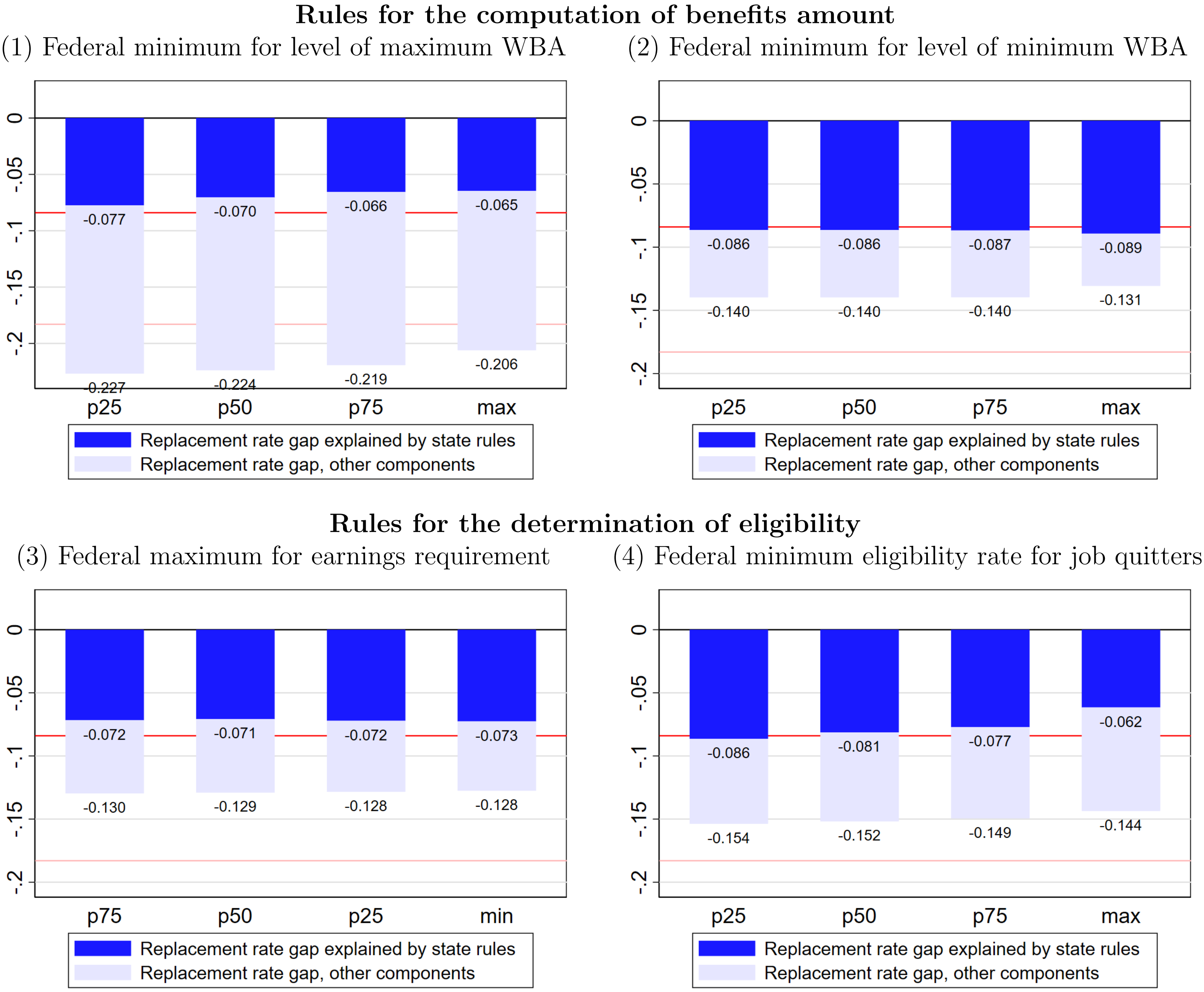


(3) **Welfare**



Notes: This Figure shows the correlation across states between the share of the Black population and various marginal welfare effects associated with a $1 transfer to unemployed workers. Panel (1) considers the marginal social value, Panel (2) considers the marginal behavioral cost, and Panel (3) considers their sum, the overall marginal welfare effect. These terms are defined following the formula in Schmieder and von Wachter (2016a), and measured using the calibration presented in Table E.1. More details are provided in Appendix E.

Figure 4: 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 rule 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 dollar values are CPI adjusted (in 2019\$).

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 Benefit Amount (in $ per week), the replacement rate (in ppt), the eligibility rate (in ppt), the Weekly Benefit 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 Benefit Amount (in $ per week), the replacement rate (in ppt), the eligibility rate (in ppt), the Weekly Benefit 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 paid 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:

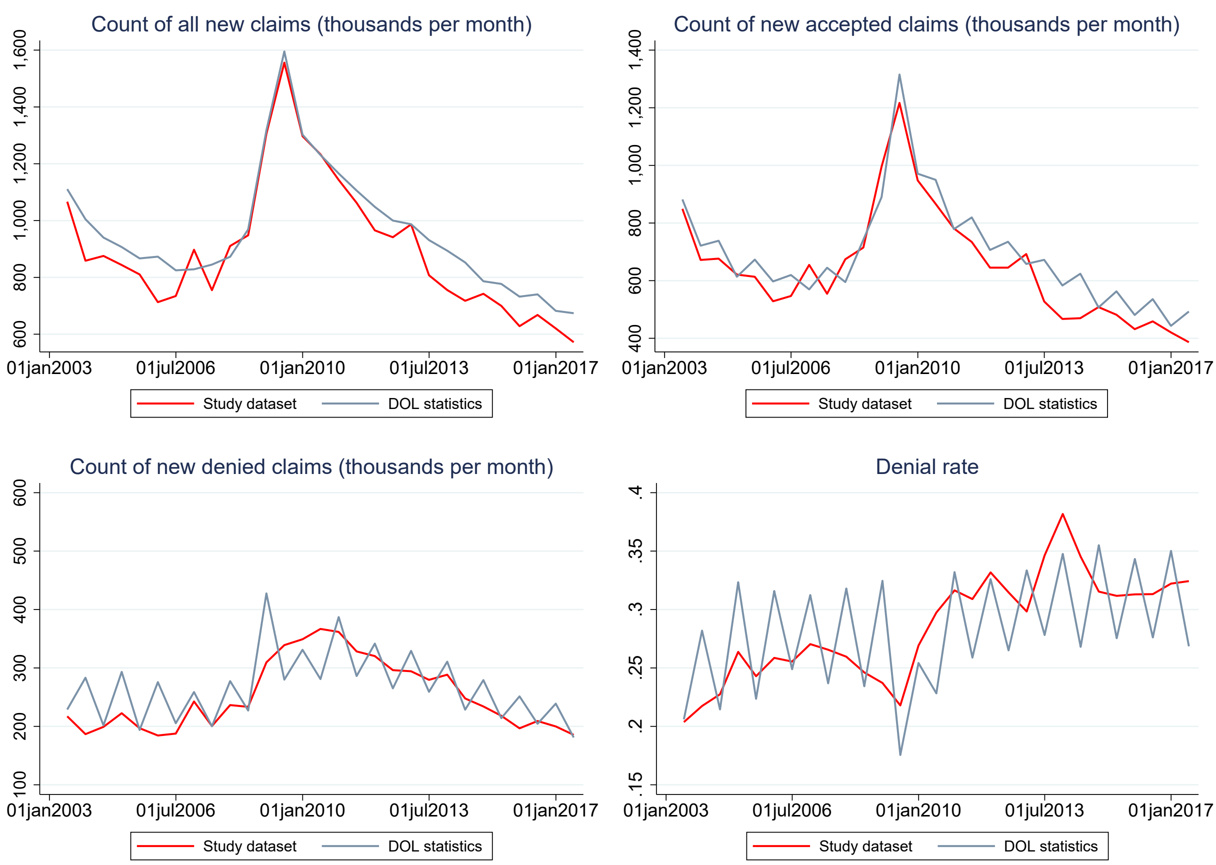


Table A.1: BAM vs. Administrative Information UI Claimants

	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").[18] 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)

[18] 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 Two methods to proxy for work history variables, in samples with missing values

When we analyze of all determinations together (results presented in Table 3), we use proxies for work history variables, to deal with missing values in parts of the sample. Here, we describe the two methods we use to build proxies for work history variables. The first method allows building proxies for the full sample of claimants, but based on less information. The second allows building proxies for the subsample of eligible claimants (i.e. either paid or monetary denied), based on richer information. Each method helps us address a different data limitation.

First method – for the "all claimants" sample 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). 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. To address this data limitation, we predict the variables relevant for monetary and separation determinations 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. But the data contains the weekly wage earned in the last job for all claims. Therefore, we predict the variables relevant for monetary determinations in the sample where these variables are non-missing, i.e. for eligible claimants and claimants denied for monetary reasons. Our prediction is 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. We use the obtained coefficients to predict monetary variables for all claims.

- For claims denied for a monetary reason, the BAM data does not report the reason for separation. 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 where the reason for separation is non-missing, i.e. for claimants that are eligible, or those denied for separation reasons. We use the obtained coefficients predict the reason for separation for all claims.

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. Note that we always use the same type of measure for all the sample considered in a given analysis: for our analysis on the full sample of claimants, we hence use proxies for all observations, even for those for which we observe the actual variables (results are unchanged if we use the actual variable when it is not missing instead).

Second method – for the "eligible claimants" sample (intensive margin) 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. 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 monetary determinations.

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. Note that we always use the same type of measure for all the sample considered in a given analysis: when we analyze racial gaps among eligible claimants, we hence use the second type of proxies for all observations, even those for which we observe the actual variables (results are unchanged if we use the actual variable when it is not missing instead).

B Decomposition of the racial gap in UI

We can rewrite the UI outcome model (equation 1) as:

$$Y_{i,k,g} = \overline{\alpha}_0 + X_i \cdot \overline{\alpha}_1 + \widetilde{\alpha}_{0,k} + X_i \cdot \widetilde{\alpha}_{1,k} + \nu_{i,k,g} \tag{B.1}$$

One can interpret $\overline{\alpha}_0 + X_i \cdot \overline{\alpha}_1$ as the UI outcome that a White claimant with characteristics X_i would obtain in the average state. $X_i \cdot \widetilde{\alpha}_{1,k} + \widetilde{\alpha}_{0,k}$ is the additional UI outcome associated with living in state k, which could be positive or negative depending on whether state k is more or less generous than the average rule, for workers with characteristics X_i.

From the UI outcome model, we derive the expected UI outcome for people in one race group $g \in \{b, w\}$ as follows (using the fact that states represent a partition of the full U.S. population):

$$\begin{aligned}
\mathbb{E}(Y|D_g = 1) &= \sum_k \mathbb{P}(S_k = 1|D_g = 1)\mathbb{E}(Y|S_k = 1 \cap D_g = 1) \\
&= \sum_k \mathbb{P}(S_k = 1|D_g = 1)\Big(\overline{\alpha}_0 + \widetilde{\alpha}_{0,k} + \mathbb{E}(X|S_k = 1 \cap D_g = 1)(\overline{\alpha}_1 + \widetilde{\alpha}_{1,k}) + \mathbb{E}(\nu|S_k = 1 \cap D_g = 1)\Big) \\
&= \overline{\alpha}_0 + \mathbb{E}(X|D_g = 1)\overline{\alpha}_1 + \mathbb{E}(\nu|D_g = 1) + \sum_k \mathbb{P}(S_k = 1|D_g = 1)\Big(\widetilde{\alpha}_{0,k} + \mathbb{E}(X|S_k = 1 \cap D_g = 1)\widetilde{\alpha}_{1,k}\Big)
\end{aligned}$$

We then derive the gap between the expected UI outcomes of Black and White claimants $\Delta = \mathbb{E}(Y|D_b = 1) - \mathbb{E}(Y|D_w = 1)$:

$$\begin{aligned}
\Delta = \overline{\alpha}_1 \cdot \Big(\mathbb{E}(X|D_b = 1) - \mathbb{E}(X|D_w = 1)\Big) + \sum_k \Bigg(\widetilde{\alpha}_{0,k} \cdot \Big(\mathbb{P}(S_k = 1|D_b = 1) - \mathbb{P}(S_k = 1|D_w = 1)\Big) + \\
\widetilde{\alpha}_{1,k} \cdot \Big(\mathbb{E}(X|S_k = 1 \cap D_b = 1)\mathbb{P}(S_k = 1|D_b = 1) - \mathbb{E}(X|S_k = 1 \cap D_w = 1)\mathbb{P}(S_k = 1|D_w = 1)\Big)\Bigg) + \mathbb{E}(\nu|D_b = 1)
\end{aligned}$$

Empirically, the UI gap can be measured by:

$$\hat{\Delta} = \hat{\overline{\alpha}}_1 \cdot (\overline{X_b} - \overline{X_w}) + \sum_k \Big(\hat{\widetilde{\alpha}}_{1,k} \cdot (\overline{S_{k,b}} \cdot \overline{X_{k,b}} - \overline{S_{k,w} X_{k,w}}) + \hat{\widetilde{\alpha}}_{0,k} \cdot (\overline{S_{k,b}} - \overline{S_{k,w}})\Big) + \hat{\nu}_b$$

where $\overline{Y_g}$, and $\overline{X_g}$, respectively denote the sample averages of UI outcomes and work history variables for each race group. $\overline{S_{k,g}} = \frac{N_{k,g}}{N_g}$ represents the fraction of people from race group g living in state k (where $N_{k,g}$ and N_g respectively denote the number of claimants in our sample from race group g living in state k and from race group g overall). $\overline{X_{k,g}}$ the sample average of work history variables for people from race group g living in state k.

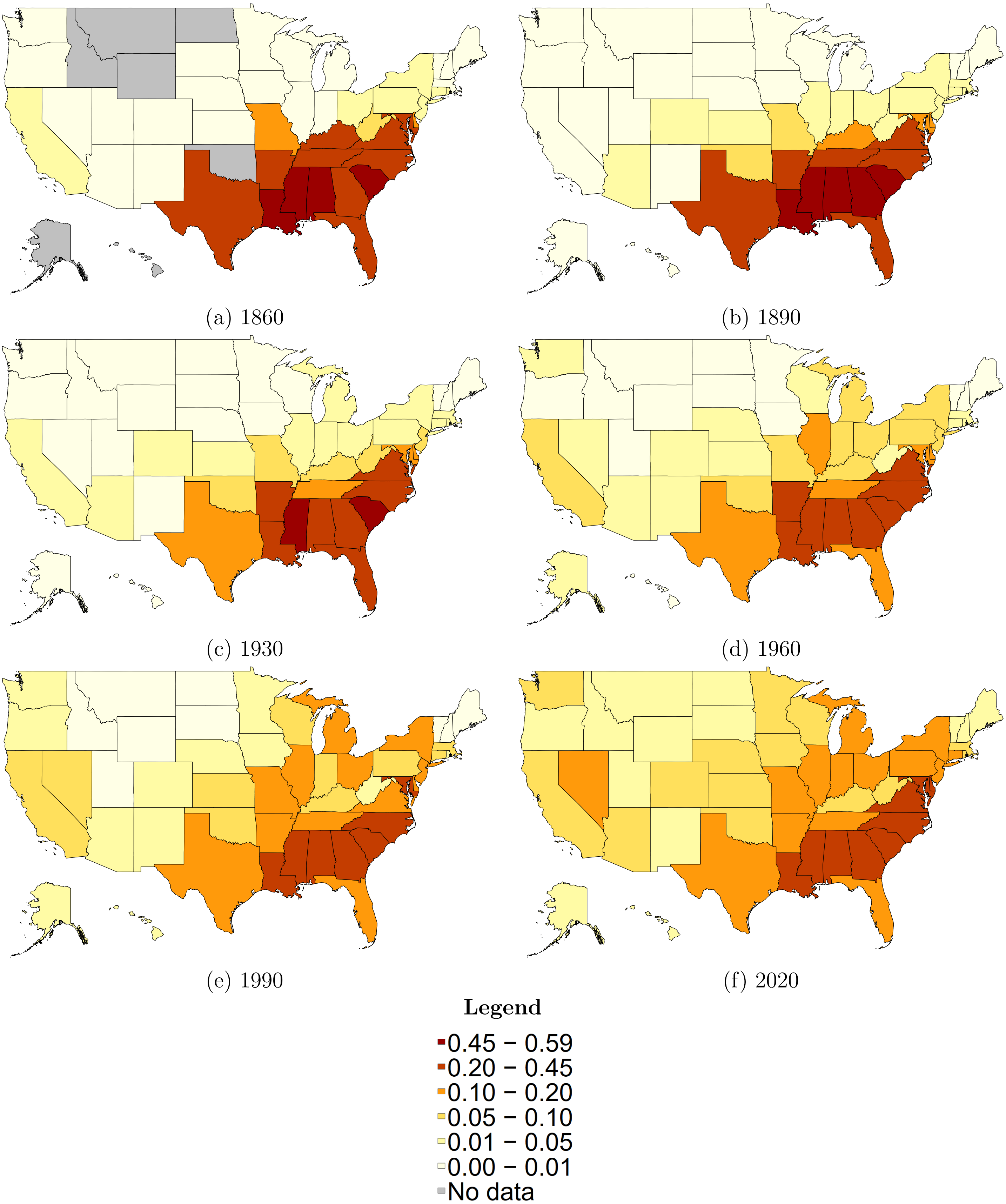
C Additional Tables and Figures

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 $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.10$.

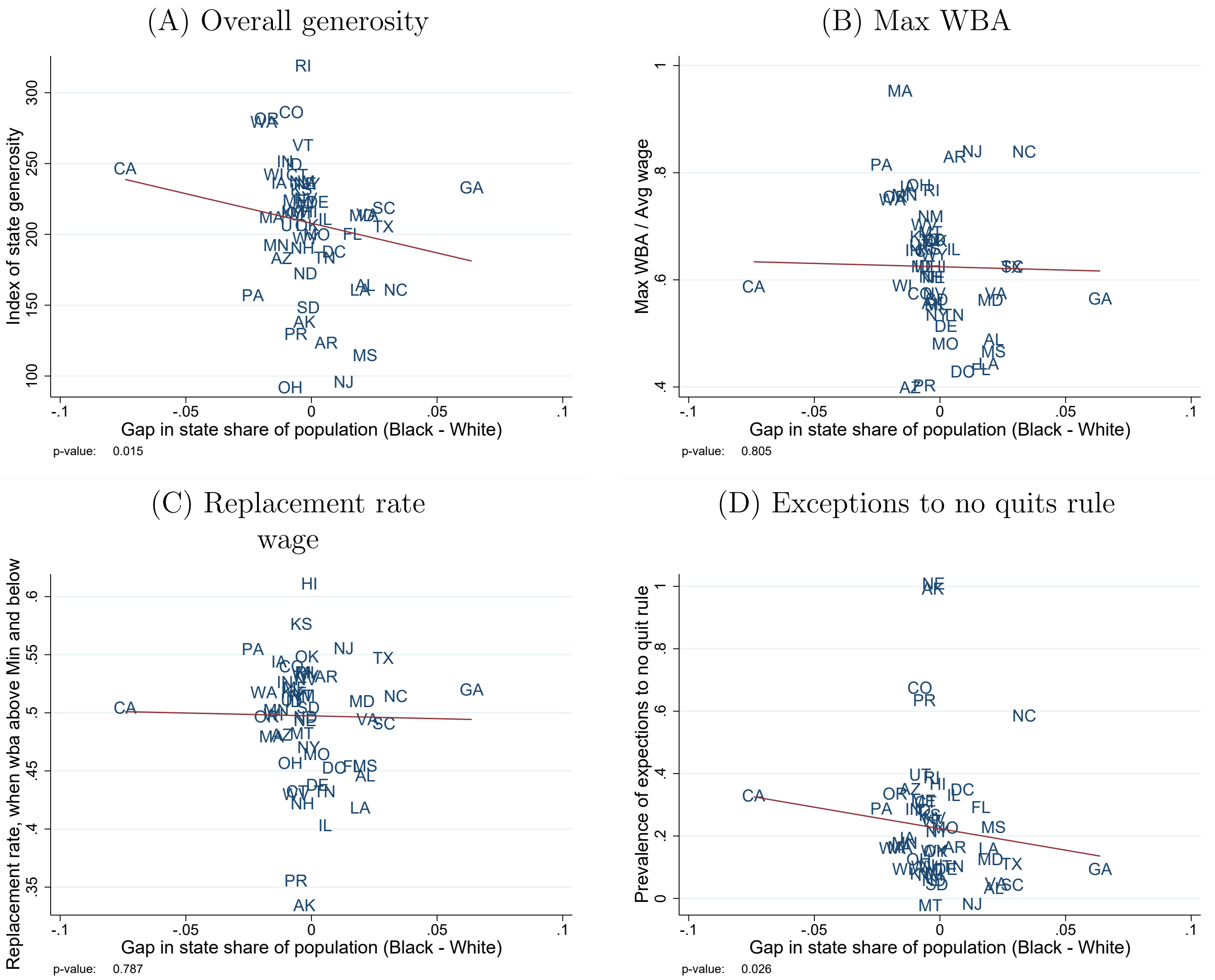
Figure C.1: Historical Black shares



(a) 1860 (b) 1890 (c) 1930 (d) 1960 (e) 1990 (f) 2020

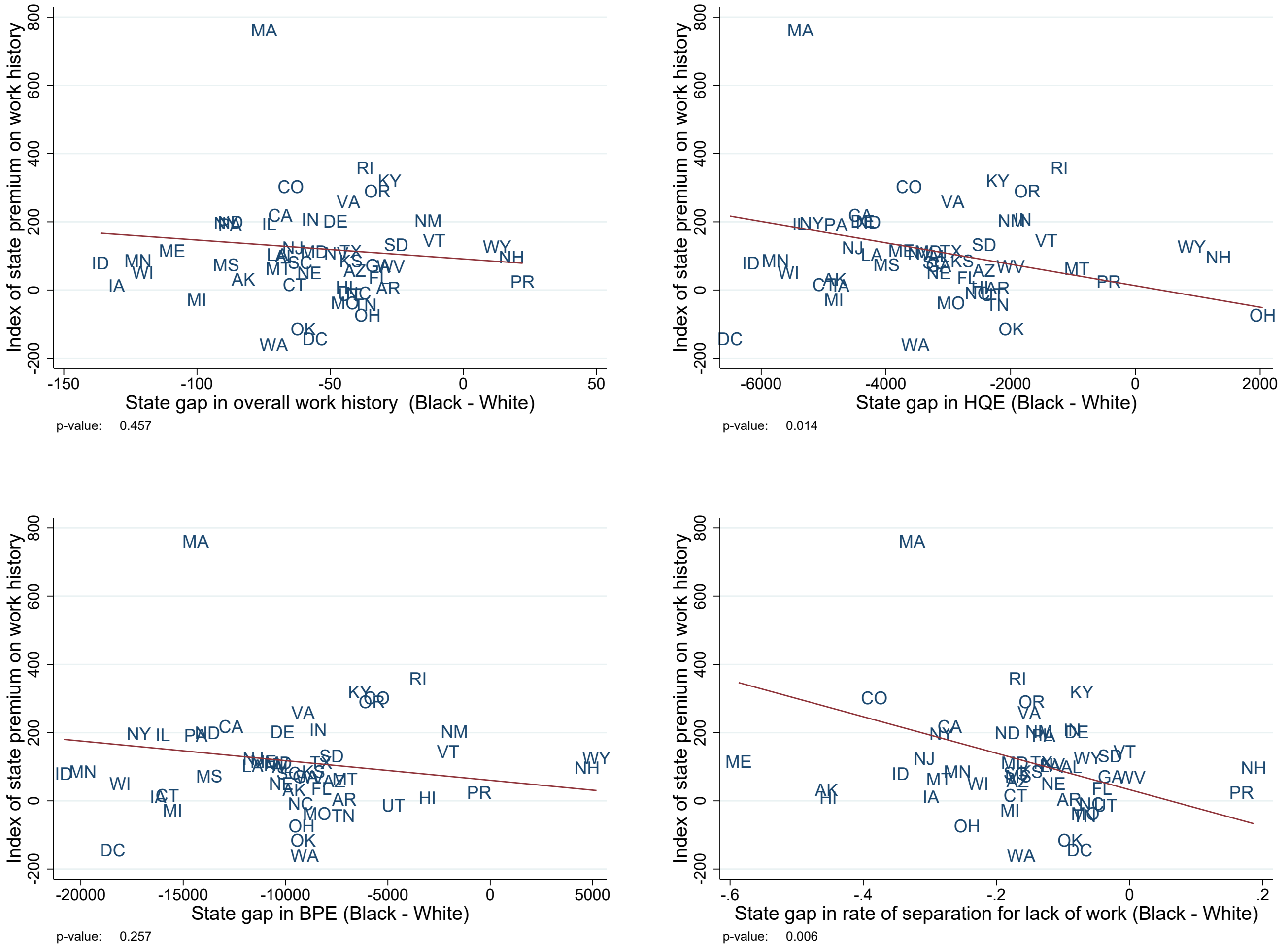
Notes: This figure shows historical Black share the population for all states from 1860 to 2020. The source data is Census Bureau estimates (Gibson and Jung, 2002).

Figure C.2: Correlation between various measures of state rules generosity, and the racial gap in the share of claimants



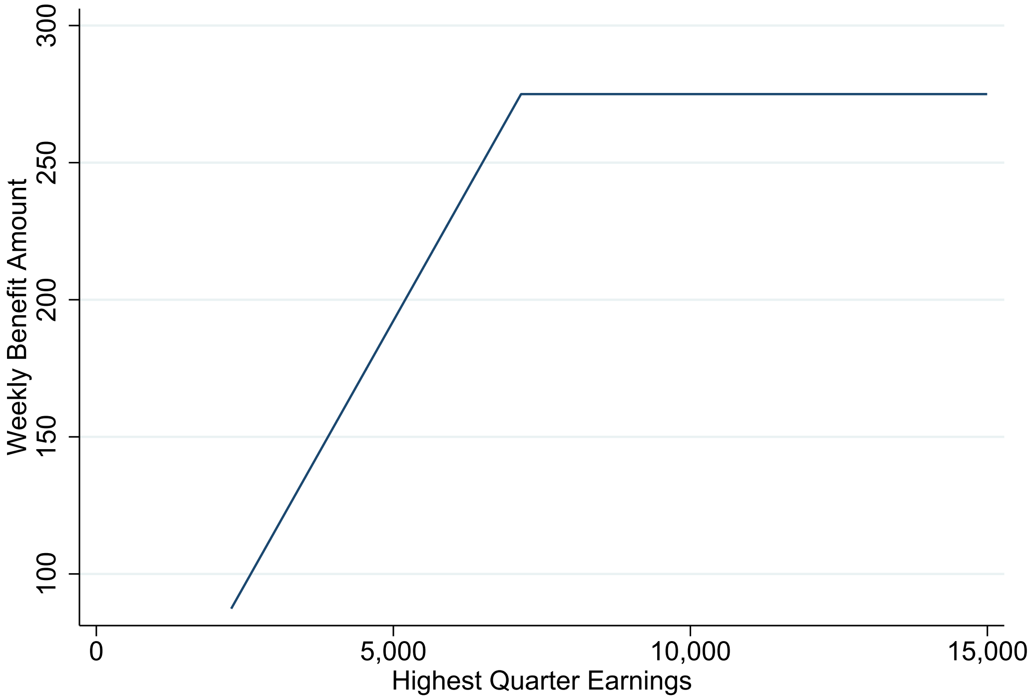
Note: This Figure presents the correlation of state rule generosity and the importance of the Black population in the state level, measured using the difference between the share of Black claimants who leave in the state minus the share of White claimant who live in the state. We measure state generosity 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.3: 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.4: 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.

Table C.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 C.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.

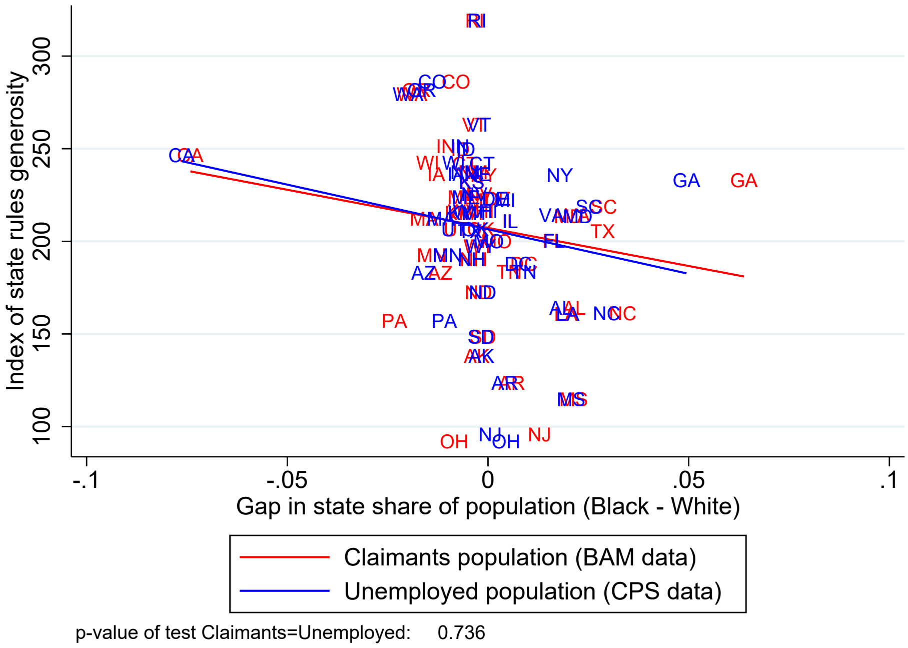
Table C.4: Black-White gaps in UI generosity overall - Estimating state rules with machine learning

	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.

Figure C.5: 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.

Table C.5: Simulated Black-White gap in UI generosity, for the full population of unemployed workers

	Actual gap among claimants		Simulated gap among unemployed			
	Week benefits (1)	Rep rate (2)	Week benefits (3)	Rep rate (4)	Week benefits (5)	Rep rate (6)
Overall explained Gap	-95.469	-0.066	-90.838	-0.062	-82.917	-0.052
(i) Explained by State Rule	-30.724	-0.030	-28.336	-0.027	-26.690	-0.025
(ii) Explained by Work History	-64.745	-0.036	-62.501	-0.034	-56.227	-0.028
White mean	274.690	0.356	270.649	0.350	270.649	0.350
Gap/White mean	-0.348	-0.186	-0.336	-0.177	-0.306	-0.149
(i)/White mean	-0.112	-0.084	-0.105	-0.078	-0.099	-0.070
(ii)/White mean	-0.236	-0.102	-0.231	-0.098	-0.208	-0.079

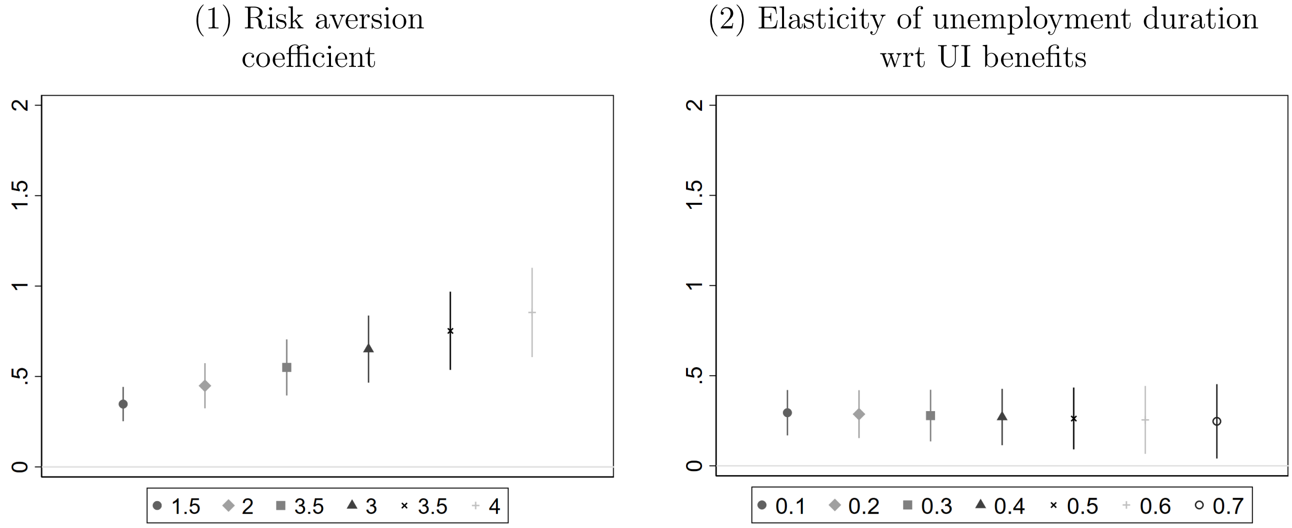
Notes: This table shows the decomposition of the actual and simulated racial gap in UI outcomes in various populations. In col (1) and (2), we consider population of BAM claimants, similar to our main analysis (Table 3). In columns (3) and (4) we consider the population of BAM claimants modified to have the same allocation of Black and White individual across states as the full population of unemployed workers (as measured in the CPS). In columns (5) and (6) we consider the population of BAM claimants modified to have the same allocation of Black and White and of work history gaps across states as the full population of unemployed workers (as measured in the CPS). The decomposition is the same as the one used in our main analysis, but we focus on the two explained components.

Table C.6: Elasticity of benefits duration and of unemployment duration with respect to replacement rate

	Log(Weeks of paid benefits)		
	(1)	(2)	(3)
Log(Replacement rate)	0.096***	0.107***	
	(0.007)	(0.009)	
Log(Replacement rate) × Share of Black		-0.056**	
		(0.024)	
Log(Replacement rate) × Q1			0.110***
			(0.008)
Log(Replacement rate) × Q2			0.086***
			(0.010)
Log(Replacement rate) × Q3			0.087***
			(0.009)
Log(Replacement rate) × Q4			0.092***
			(0.009)
Elasticity of unemployment duration	0.097	0.108	
Elasticity of unemployment duration in Q1			0.111
Elasticity of unemployment duration in Q2			0.087
Elasticity of unemployment duration in Q3			0.088
Elasticity of unemployment duration in Q4			0.093
Nb of observations	347,884	347,884	347,884

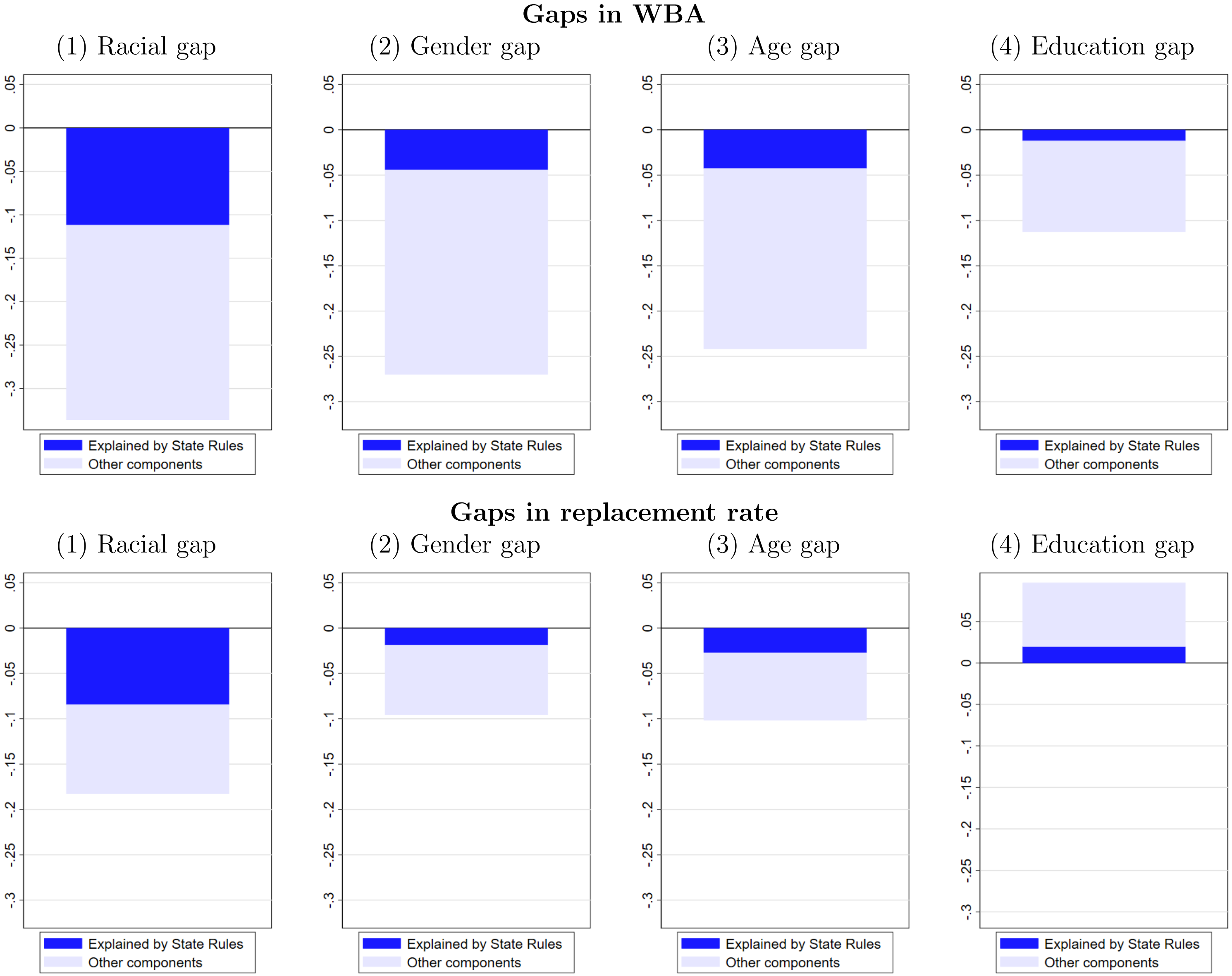
Notes: In this Table, we present the results from the regression of the log of weeks of paid benefits on the replacement rate, including year fixed effects, state fixed effects and a wide range of individual controls: reason for separation, base period earnings, number of employers in the base period, recall status, potential benefits duration, prior wage deciles, race, gender, education level, age, citizenship status, prior occupation fixed effects, industry fixed effects. The variation in the replacement rate used for identification comes from differences across states in the formula used to compute benefits, differences in individual highest quarter earnings, and non linearities in the formula. In contrast with the rest of the paper, we conduct this regression in the full sample of paid claimants: not only those newly eligible. In column (1), the coefficient associated with the log of the replacement rate gives the estimate for the elasticity of benefits duration with respect to replacement rate. In column (2), we estimate an additional coefficient for the interaction of the log of the replacement rate and the share of Black claimant in the state. In column (3), we estimate a separate elasticity for claimants in states in different quartile of the distribution of the share of Black claimants (Q1 are the states with the smallest fraction of Black claimants while Q4 are the states with the largest fraction). In the bottom part of the Table, we re-scale the estimates for the elasticity of *benefits* duration with respect to replacement rate to obtain an estimate for the elasticity *unemployment* duration, using the state average exit rate, maximum benefits duration and the share of unemployed workers who remain unemployed longer than the maximum duration (see Appendix Section E.2)

Figure C.6: Correlation between the marginal welfare effect of a UI increase and the share of Black claimants, for alternative calibrations



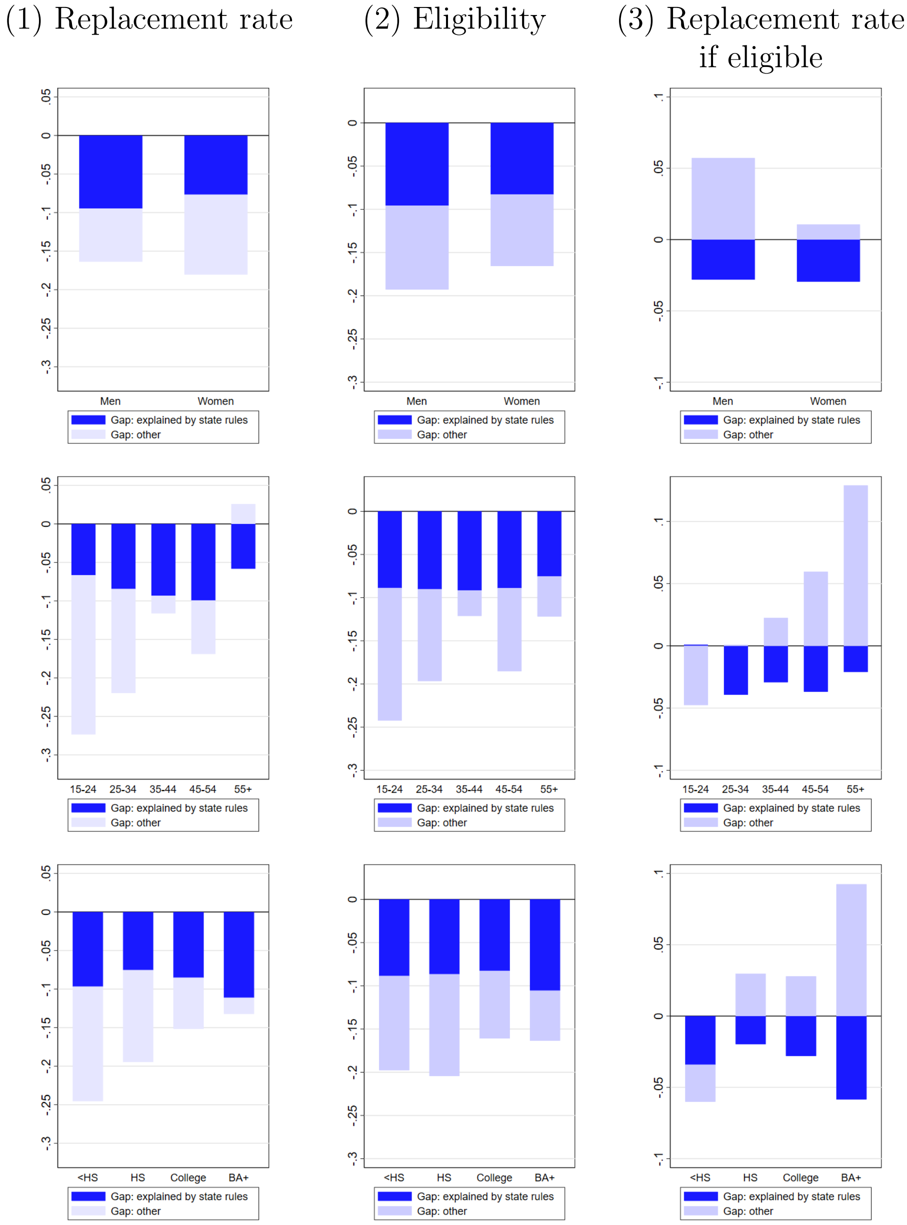
Notes: These Figures present the marginal welfare effect of a UI, using the same calibration as that presented in Table E.1, except for the values of the risk aversion coefficient in Panel (1), and of the elasticity of unemployment duration with respect to benefits in Panel (2).

Figure C.7: 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 Benefit 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 rule differences.

Figure C.8: Heterogeneity in the racial gaps, across gender, age, education groups



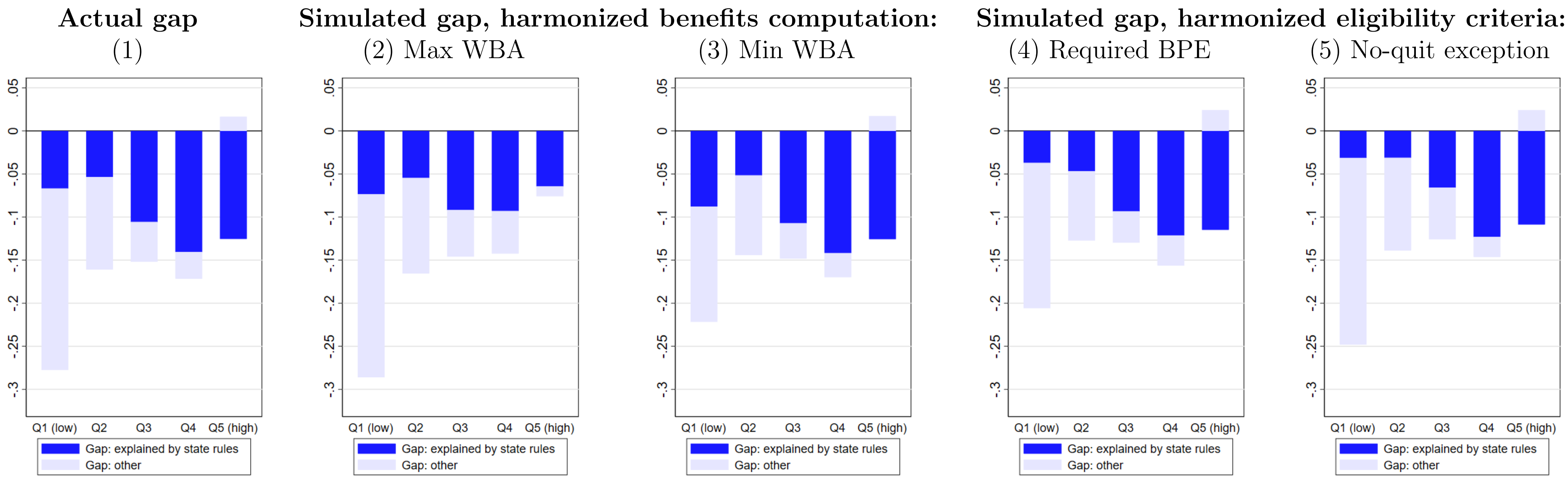
Note: We present the Black-White gaps explained by state rule differences for three outcomes: replacement rate, eligibility (extensive margin), replacement rate if eligible (intensive margin). The y-axis represent the magnitude of the relative gaps in %. We show separately the gaps for men and women,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

Table C.7: Mistakes (original value - value determined after BAM audit) in the assessment of UI outcomes variables

	WBA			Replacement rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Black	-1.608	-0.358	-1.195	-0.007***	-0.002	-0.004***
	(1.019)	(1.292)	(0.754)	(0.002)	(0.002)	(0.001)
Female		2.152***	1.892***		0.001	0.001
		(0.499)	(0.521)		(0.001)	(0.001)
Age: 25-34		-1.082	-1.491		0.001	0.001
		(1.238)	(1.293)		(0.002)	(0.002)
Age: 35-44		-1.223	-1.567		0.003	0.003
		(1.512)	(1.465)		(0.002)	(0.002)
Age: 45-54		-0.586	-1.016		0.004*	0.004*
		(1.335)	(1.290)		(0.002)	(0.002)
Age: $\geq$ 55		1.822	1.056		0.009***	0.008***
		(1.172)	(1.402)		(0.002)	(0.002)
Educ: HS degree		0.192	-0.839		0.001	-0.001
		(0.699)	(1.278)		(0.001)	(0.002)
Educ: Some college		-2.304*	-2.576*		-0.001	-0.001
		(1.253)	(1.464)		(0.001)	(0.002)
Educ: College degree		-1.074	-2.035		0.004***	0.003
		(1.284)	(1.789)		(0.001)	(0.002)
Occup & Ind FE		×	×		×	×
State FE			×			×
N	168,868	168,859	168,859	168,821	168,812	168,812

Notes: This table presents the correlation of mistakes in the assessment of UI outcomes. 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 Benefit Amount, and in replacement rate. We report robust standard errors clustered at the state level.

Figure C.9: Heterogeneity in the actual and simulated racial gaps, across prior wage quintile

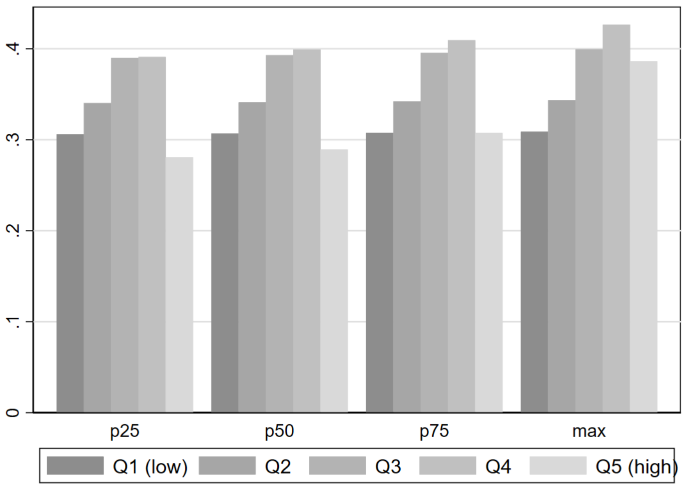


Note: We present the gap in replacement rate obtained if we harmonized each of the four policy parameter considered (set to the maximum generosity level). The y-axes always represent the magnitude of the relative gaps in %. We show separately the gaps for claimants in various quintiles of the distribution of hourly wage before job loss (below \$10.7, 10.7-13.9, 13.9-18.1, 18.1-25.9, above \$25.9).

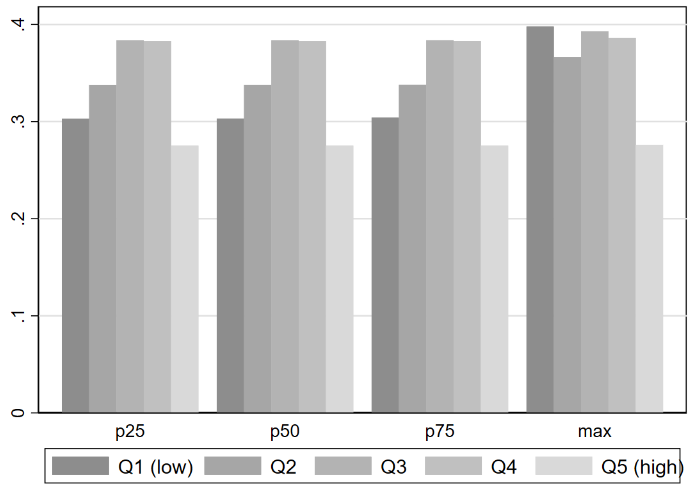
Figure C.10: Policy simulation

Rules for the computation of benefits amount

(1) Federal minimum for level of maximum WBA

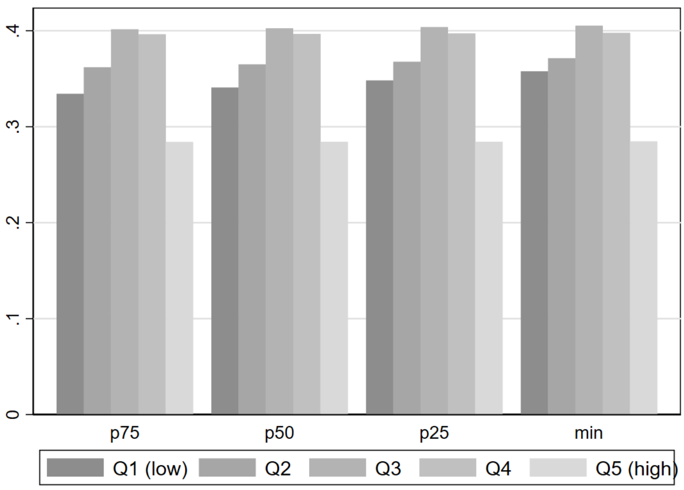


(2) Federal minimum for level of minimum WBA

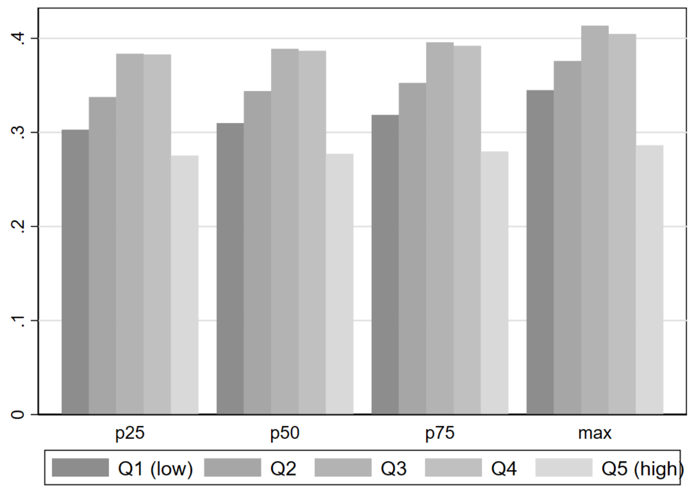


Rules for the determination of eligibility

(3) Federal maximum for earnings requirement

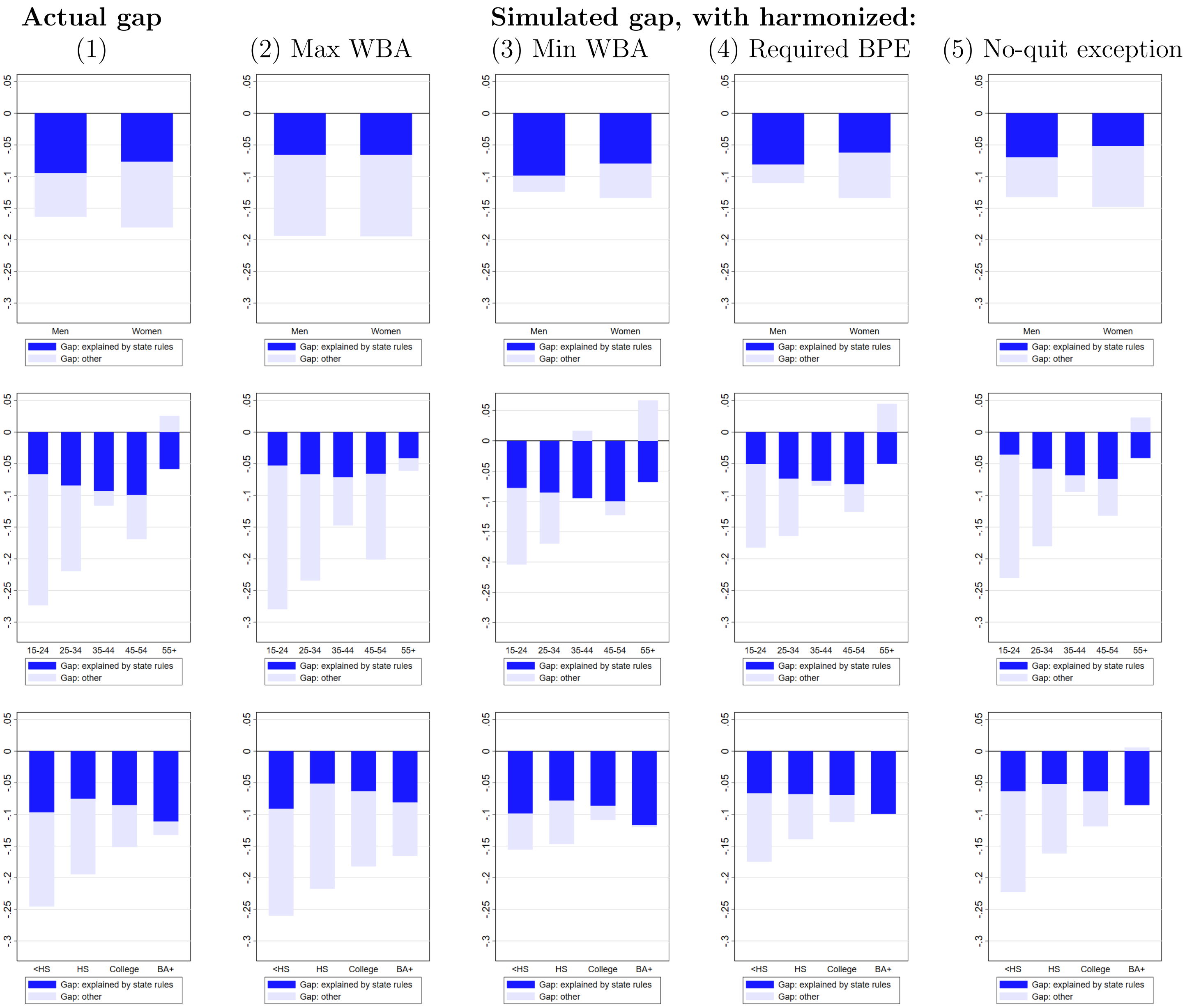


(4) Federal minimum eligibility rate for job quitters



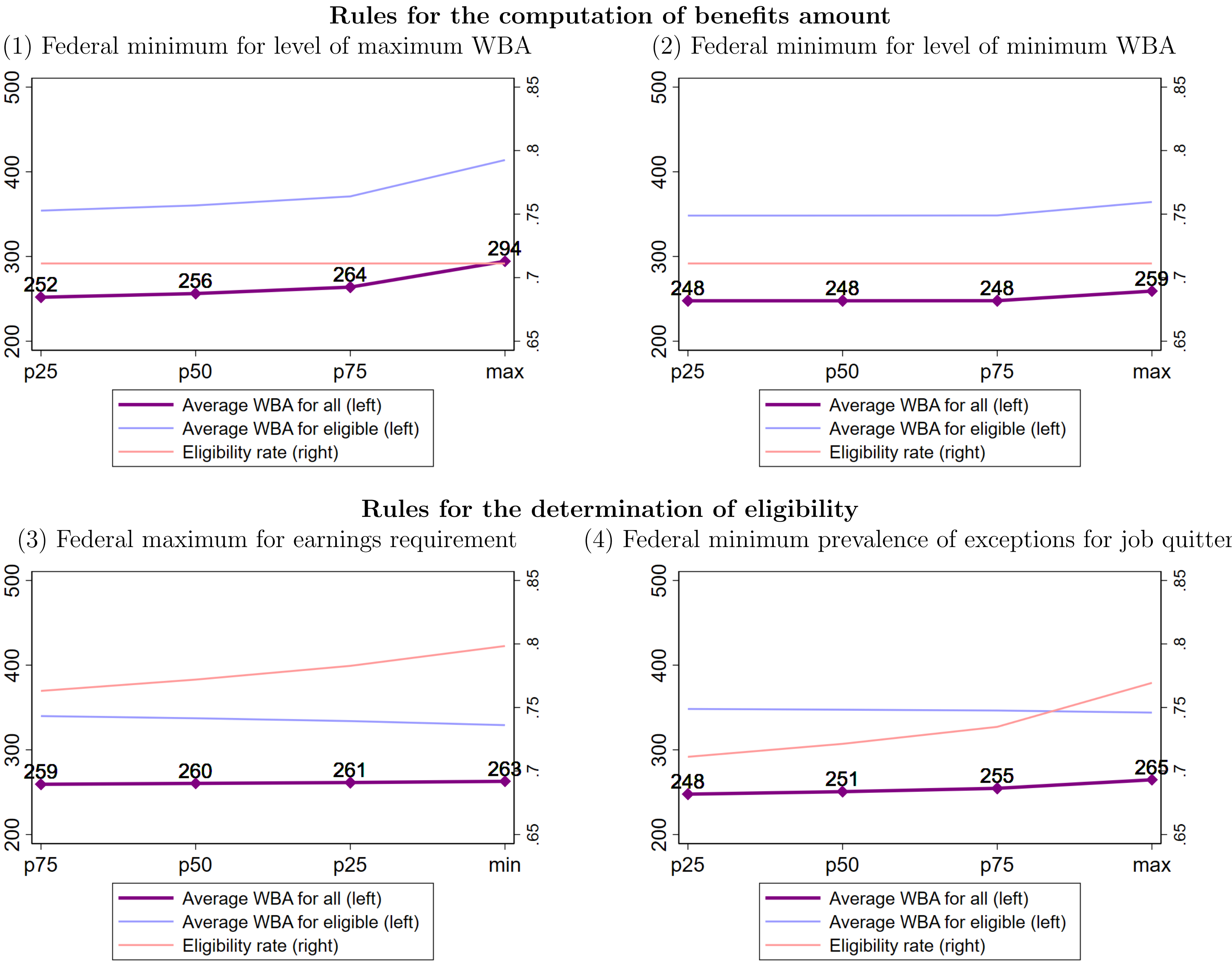
Notes: We present the simulated replacement rate for claimants with prior wages in different quintiles of the prior wage distribution, under different hypothetical policy reforms. We consider the same policy reforms as in Figure C.10: we harmonize the cap on WBA (in (1)), the minimum level of WBA (in (2)), the minimum BPE required for eligibility (in (3)), and the rate of eligibility for job quitters (in (4)).

Figure C.11: Heterogeneity in the actual and simulated racial gaps, across gender, age, education groups



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).

Figure C.12: Policy simulation



Notes: In this Figure, the thick line represents the simulated average Weekly Benefit Amount among all UI claimants, under different hypothetical policy reforms. We also present the simulated average Weekly Benefit Amount among eligible claimants, and the simulated eligibility rate. We consider the same policy reforms as in Figure C.10: 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)).

D Comparison of claimants & unemployed workers

If all unemployed claimed for UI, the same process would determine their UI outcomes, based on their state, their work history, and potentially their race group, as described in model 1. An estimate for the gap in expected UI outcome among unemployed can be obtained as (with the superscript u standing for the sample means in the population of unemployed workers):

$$\hat{\Delta}^u = (\overline{X_b^u} - \overline{X_w^u})\hat{\alpha}_1 + \sum_k \left((\overline{S_{k,b}^u} - \overline{S_{k,w}^u}) \cdot (\overline{X_{k,b}^u} \cdot \hat{\hat{\alpha}}_{1,k} + \hat{\hat{\alpha}}_{0,k}) + (\overline{X_{k,b}^u} - \overline{X_{k,w}^u}) \cdot \overline{S_{k,w}^u} \cdot \hat{\hat{\alpha}}_{1,k} \right) + \sum_k \overline{S_{k,b}^u} \cdot \hat{\nu}_{k,b}$$

Remember that (from equation 2 and 3):

$$\hat{\Delta} = (\overline{X_b} - \overline{X_w})\hat{\alpha}_1 + \sum_k \left((\overline{S_{k,b}} - \overline{S_{k,w}}) \cdot (\overline{X_{k,b}} \cdot \hat{\hat{\alpha}}_{1,k} + \hat{\hat{\alpha}}_{0,k}) + (\overline{X_{k,b}} - \overline{X_{k,w}}) \cdot \overline{S_{k,w}} \cdot \hat{\hat{\alpha}}_{1,k} \right) + \sum_k \overline{S_{k,b}} \cdot \hat{\nu}_{k,b}$$

Therefore, $\hat{\Delta}^u$ and $\hat{\Delta}$ could be different because of four potential factors:

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

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

(iv). $\sum_k \overline{S_{k,b}^u} \cdot \hat{\nu}_{k,b} \neq \sum_k \overline{S_{k,b}} \cdot \hat{\nu}_{k,b}$, i.e. the unexplained gap is different

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 and (iv) for the size of the unexplained gap. First, we merely discuss whether we should expect the estimated gap explained by state rule differences among unemployed and among claimants to differ, based on descriptive statistics from the BAM data and the CPS. Second, we provide our best estimate for the gap explained by state rule differences among unemployed workers, using the combination of these datasets.

E Marginal welfare effect of UI benefits, state by state

E.1 Formula for the marginal welfare effects of UI transfer:

Following Schmieder and von Wachter (2016a), we can compute for each state the marginal welfare effect of increasing the transfers to the unemployed by \$1:

$$\frac{dW}{db}\frac{1}{B\nu'(c_e)} = \underbrace{\frac{u'(c_{u,t\leq P}) - \nu'(c_e)}{\nu'(c_e)}}_{\text{Social value}} - \underbrace{\left(\eta_{B,b} + \eta_{D,b}\frac{D}{B}\frac{\tau}{b}\right)}_{\text{Behavioral cost}} \tag{E.1}$$

where W denotes welfare (i.e. the lifetime expected utility of an individual), b is the per period benefit amount received by workers who are unemployed for less than the maximum benefits duration, τ represents the per period tax paid by employed workers, B represents the expected duration of UI receipt, D the expected duration of unemployment, $\nu'(c_e)$ represents the marginal utility of employed workers, P the potential benefits duration, $u'(c_{u,t\leq P})$ the marginal utility of unemployed workers who have not yet exhausted their benefits, $\eta_{B,b}$ the elasticity of benefits duration with respect to the benefits amount, and $\eta_{D,b}$ the elasticity of unemployment duration with respect to the benefits amount.

On the left hand side, $\frac{dW}{db}$ is the marginal effect of increasing the level of UI benefits by \$1. Because an additional \$1 of UI generates a mechanical transfer of \$$B$ (\$1 for B periods) for each unemployed worker, $\frac{dW}{db}\frac{1}{B}$ is the marginal effect of an increase by \$1 in the per period *transfers* to the unemployed. Finally, $\frac{dW}{db}\frac{1}{B\nu'(c_e)}$ is the marginal effect of an increase by \$1 in the transfers to the unemployed, in the unit of a \$1 increase in consumption to the employed. On the right-hand side, the first term captures the social value from smoothing the income levels between the unemployed and the employed states of the world. The larger it is, the larger the marginal welfare gain from increased UI transfers. The second term captures the costs associated with workers staying unemployed longer: longer unemployment duration is associated with additional benefits transfers ($\eta_{B,b}$), and with fewer taxes collected ($\eta_{D,b}\frac{D}{B}\frac{\tau}{b}$). Schmieder and von Wachter (2016a) show that, under reasonable assumptions, this cost can be approximated by the following expression, which is typically easier to measure (S_P the share of unemployed workers who exhaust their benefits, and s the constant exit rate out of unemployment):

$$\eta_{B,b} + \eta_{D,b}\frac{D}{B}\frac{\tau}{b} = \eta_{D,b} \cdot \frac{1}{1 - S_P} \cdot \left(1 - (1 + sP)e^{-sP} + \frac{\tau}{b}\right)$$

Note that for simplicity, we consider that changes in benefits across states entirely come from difference in benefits levels: we take the average benefits received by unemployed workers with duration lower than the maximum benefits duration. We do not differentiate between differences coming from eligibility rules and those coming from the benefits levels for eligible workers.

E.2 Calibration:

Table E.1: Welfare calibration for each state and each year

	Mean	Min	Max	Std.Dev.
A/ Statistics from various sources				
Total UI taxes in each state, year (millions)	702.95	32.53	4892.30	890.68
Total UI benefits in each state, year (millions)	741.59	31.53	5851.34	992.80
Maximum potential benefits duration (weeks)	25.77	22.26	30.00	1.14
Rate of benefits exhaustion	0.23	0.14	0.34	0.05
Exit rate out of unemployment	0.09	0.07	0.13	0.01
Income of employed (weekly)	900.07	753.32	1347.14	113.78
Income of unemployed for less than max PBD (weekly)	376.93	272.32	504.13	58.21
B/ Calibrated parameters				
Risk aversion coefficient	2.00	2.00	2.00	0.00
Elasticity of unemployment duration wrt benefits	0.38	0.38	0.38	0.00
C/ Welfare calibration				
Social value calibration	1.06	0.89	1.26	0.09
Behavioral cost calibration	0.39	0.34	0.43	0.02
Welfare effect calibration	0.67	0.49	0.90	0.10

Main statistics We approximate for each state the marginal welfare effects, using the aggregate statistics reported in Table E.1, Panel A:

- We use publicly available information on the total UI tax collected (to measure τ) and the total benefits (to measure b) distributed by each state each year. We collect information on the maximum benefits duration (in weeks) for each state and each year from state UI laws (P).
- Then, for each state, we measure in the CPS the weekly exit rate out of unemployment (s) and the fraction of workers staying unemployed at least until the end of the maximum benefits duration (S_P).
- To capture the incomes of employed vs. unemployed workers, we measure the average earnings of employed workers and of workers who have been unemployed less than the maximum benefits duration in the ASEC, and assume that workers consume in each week their weekly income (yearly income converted weekly). Alternatively, we use the income measures from the Survey of Income and Program Participation (SIPP): because it is a monthly panel, it allows us to measure the income drop around a change in employment status at the individual level.

Measures of consumption smoothing It is notoriously hard to measure the social value of a benefits increase. Following the literature (Baily, 1978b; Gruber, 1997; Chetty, 2006; Kroft and Notowidigdo, 2016b), we approximate the gap in marginal utilities of consumption by the difference in consumption between the employed and the UI recipients multiplied by the coefficient of risk aversion (γ):

$$\frac{u'(c_{u,t\leq P}) - \nu'(c_e)}{\nu'(c_e)} \approx \gamma \cdot \frac{c_e - c_{u,t\leq P}}{c_e}$$

Moreover, as there is no dataset that allows to track changes in consumption around unemployment at the state level, we use the change in income as an approximation for the change in consumption (similar to Leung and O'Leary (2020)). That should lead us to overestimate the social value of a benefits increase, as consumption should drop less than income. We therefore abstain from interpreting the magnitude of the welfare effects of benefits increases. However, we can interpret the cross-state correlation between marginal welfare effects and the share of Black claimants, to the extent that differences between the drop in incomes and the drop in consumption levels are similar across states. We note that the finding by Ganong et al. (2021) that the consumption of Black workers drops *more* than that of White workers facing a similar income shocks suggests that, if anything, the drop of consumption (and hence the social value of UI) should *be even larger* in states with a higher share of Black population than what our estimates suggest.

We use the standard value $\gamma = 2$ for the coefficient of risk aversion in our main calibration (Panel B). This calibration allows us to obtain a measure of the social value of a 1 \$ increase in benefits, reported in Panel C. We show that our conclusions remain unchanged for alternative values (Figure C.6 (1)). Results also remain similar if we compare the differences in income between unemployed and employed at the population level (using ASEC data), or for the same individuals (using SIPP data).

Measures of the elasticity of unemployment duration wrt UI level Empirical assessments of the welfare effects of UI typically focus on the measure of this elasticity. While there are many estimates for this elasticity for the U.S., there are no systematic state-level estimates. Therefore, we first use for our main calibration the value $\eta_{D,b} = 0.38$, i.e. the median of the estimates in the literature (Schmieder and von Wachter, 2016a), and show that our conclusions remain unchanged for alternative values. Although assuming that the duration elasticity is the same across states might miss important aspects of this welfare calculation, it is a useful benchmark, as it reflects the current state of knowledge, for academics or policy makers. Figure C.6 shows that this result holds with alternative parameter values for the elasticity of unemployment duration with respect to benefits.

Second, we test empirically if the elasticity of unemployment duration wrt UI level changes with the state-level share of Black claimants. The BAM data are ideally suited to estimate the effect of UI across states, since it is one of the rare datasets covering all U.S. states with detailed information on UI and for large samples of workers. We don't observe the full duration of unemployment for BAM claimants, only the duration until the audit. Since the time of the audit is random, we can back out the elasticity of *paid benefits duration* with respect to benefits level ($\eta_{B,b}$), from the elasticity of paid benefits before an audit. Then, following (Schmieder and von Wachter, 2016a), we can easily compute the elasticity of *unemployment duration*, under the assumption that the exit rate of unemployment, s, is constant. Assuming that D has exponential (s) distribution, we can write:

$$\eta_{B,b} = \eta_{D,b} \cdot \frac{1}{1 - S_P} \cdot \left(1 - (1 + sP)e^{-sP}\right)$$

In Table C.6, we find that the elasticity of benefits duration with respect to the replacement rate decreases with the share of Black claimants in the state. This implies that the marginal welfare costs due to behavioral effects are even lower in states with a high share of Black claimants. Therefore, allowing for different elasticities across states reinforces our conclusion that the marginal welfare effects of increasing unemployment benefits are higher in states with a larger share of Black claimants.