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Racial Inequality in the U.S. Unemployment Insurance System

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Abstract

The decentralized US unemployment insurance (UI) system lets states decide on key rules. Decentralization could help states efficiently adapt to local economic conditions, but it could also generate racial inequality. We build a novel nationally representative dataset of UI claimants and document a 18.3% gap in UI entitlements between Black and white claimants. After accounting for claimants' work history, we show that state rules differences alone create a 8.4% racial gap. Yet, our welfare analysis indicates that state rules differences are inefficient. Reducing UI rule disparities across states would thus enhance both racial equity and economic efficiency.

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"...from a Negro's point of view it [the Social Security Bill that created Unemployment insurance in the U.S.] looks like a sieve with the holes just big enough for the majority of Negroes to fall through."

Charles Houston, representing the National Association for the Advancement of Colored People (NAACP), in front of the U.S. Senate in 1935.

1 Introduction

Given large racial economic disparities in the U.S., Black Americans are especially vulnerable to negative economic shocks. In particular, Black workers experience additional difficulties when they lose their job, since they face discrimination in hiring (Kline, Rose, and Walters, 2021) and hold little liquid wealth (Ganong et al., 2021). Institutions like Unemployment insurance (UI) are critical to alleviate racial inequality. However, institutions can treat Black and white beneficiaries unequally, despite being nominally race-neutral. A key concern dating back to the founding of UI is its decentralized structure, which leaves states considerable autonomy in setting rules on the eligibility criteria and benefits amount. On the one hand, decentralization might be more efficient if it allows states to tailor UI rules to their specific labor market conditions. On the other hand, decentralization might create racial inequality if states with larger Black populations systematically choose more stringent rules.[1] In this paper, we analyze the differences in UI rules that have emerged across states: Do they create a gap in the insurance that Black and white unemployed workers can receive? And are they efficient, i.e. would a race-neutral central planner choose similar state rules differences? Ultimately, we find that state differences in UI rules generate both racial inequality and inefficiency. Since we find no equity-efficiency trade-off, our results lend support to policies that reduce the differences in UI generosity across states.

Assessing whether disparate state rules generate racial inequality in UI entitlements is less straightforward than might seem. Since states decide on many UI rules, it is necessary to systematically consider *all* rules, otherwise one could worry that states that have stricter rules in one dimension (e.g., lower cap on weekly benefits) have more lenient ones in other dimensions (e.g., lower earnings requirement for eligibility). Moreover, differences in rules only matter if they are binding for some people (e.g., a low cap on benefits only matters if it is below the benefit amount that some people could receive). We hence need detailed microdata for the population of claimants, with the individual characteristics that are

[1]The federal-state structure voted in 1935 was criticized by many African American leaders from the start. They defended an alternative proposal for a national system paid by the federal government, the Lundeen plan. See Lieberman (2001a) and Katznelson (2006) for discussions about how the decentralized design of Unemployment Insurance and other social programs created in the 1930s-1940s (like the Aid to Dependent Child) might have contributed to exclude Black people. The authors also discuss how other features of the UI system voted in 1935 contributed to exclude Black workers, like the exclusion of agricultural and domestic occupations. We provide additional details in Section 2.1.

relevant for the UI administration—we will refer to these variables through the paper as "work history." There are two types of work history variables considered by the UI administration: monetary variables (earnings and weeks worked in quarters before job loss), and separation variables (reason from separation from last employer). Gathering this information is a challenge, as there are key limitations in both the administrative data (e.g., Lachowska, Sorkin, and Woodbury (2021)) and the survey data (e.g., Kuka and Stuart (2021)) used in prior literature. UI administrative data is collected separately in each state and not consolidated at the federal level. Moreover, in some states, these data do not contain information on race. In survey data, relevant aspects of individual work history can be misreported, and the available variables never exactly correspond to the ones used by the UI administration. An even more fundamental issue is the large under-reporting of UI receipt in survey data: the SIPP undercounts aggregate UI benefits by 40% (Meyer, Mok, and Sullivan (2015)), and the CPS undercounts the number of UI recipients by 50%, with the largest gaps for lower income deciles (Larrimore, Mortenson, and Splinter (2022b,a)).

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. The BAM program has required all states to conduct audits among paid and denied claims since 2002. Importantly, the claims to be audited are randomly sampled, allowing for inference on the general population. Unlike prior research using the BAM data, we analyze not only audits of paid claims, but also audits of denied claims. Combining these audits, we construct a representative sample of all UI claimants for the entire U.S from 2002 to 2017—the first to our knowledge. Having a dataset representative of all UI claimants allows us to study both the racial gap in benefit amount for eligible workers (i.e. the intensive margin), and the gap in the eligibility rate (i.e. the extensive margin). In contrast with UI administrative data used in prior research, the BAM data covers all U.S. states and contains rich demographic information on claimants in all states: all audited claimants fill a standardized questionnaire where they report their race and ethnicity. In contrast with survey data, the BAM data contain the exact work history variables that are used by the UI administration: they come from administrative wage registers, claimants and employers declarations, and are hand-checked by auditors. Concerns over mis-reporting that plague other sources are hence particularly low.

Our representative sample of UI claimants gives us a unique opportunity to describe the claiming process. Strikingly, we see that 28% of new claimants are found ineligible. The replacement rate (i.e. unemployment benefits relative to prior earnings) 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 large racial gap in the outcome of claims. The eligibility rate is 61% for Black claimants, and 76% for white claimants. Overall, Black claimants receive a 29% replacement rate when accounting for denials, while the equivalent replacement rate is 36% for white claimants: the replacement rate for Black claimants is hence 18.3% lower than for white claimants. Various factors might contribute to this gap. In particular, we observe that Black claimants have a less favorable work history when they lose their job (e.g., lower earnings in the preceding quarters), consistent with prior evidence of racial inequality in the labor market. Our next analysis aims to isolate the contribution of state rule differences to the racial gap in claimants' replacement rate.

Our empirical method proceeds in two steps. First, we estimate the full set of relevant state-specific UI rules. the UI benefits received by claimants mechanically depend on the rules in their state and on their work history. We observe the work history variables used by the UI administration to determine claimants' benefits. We are hence in the unique situation where we can regress UI outcomes on all the relevant explanatory variables and recover their causal effects, i.e. the UI rules parameters. In practice, we estimate state by state the relation between various UI outcomes and a flexible function of work history, in the population of white claimants only. In a second step, we use the estimated UI rule parameters to decompose the racial gap in the UI received by claimants (Kitagawa (1955)-Oaxaca (1973)-Blinder (1973)). This allows us to separate the contribution of two distinct factors: the racial differences in claimants' work history, and the differences in the rules prevailing in claimants' states.[2] Any residual gap after accounting for these two factors would suggest either that there is discrimination in the implementation of the rules or that we fail to correctly include all the relevant explanatory variables. Under the assumption that we adequately include all the relevant explanatory variables, our decomposition identifies the contribution of these variables to the racial gap in the UI received by claimants in a *causal sense* (rather than in a statistical sense only). We provide numerous tests supporting our identifying assumption. In our main analysis, one potential limitation is that we use proxies for the work history variables that are missing for a small fraction of claimants. We show that our results are robust by reproducing our empirical analysis focusing on UI rules related to monetary work history only, for which we fully observe the relevant work history variables.

Do state rule differences contribute to the 18.3% gap in replacement rate between Black and white claimants? We find that racial differences in work history cause a 10.2% gap, accounting for a little over half of the difference in the replacement rate. Though the gap explained by work history differences is large, it is striking that another large part of the racial gap in UI is *not* explained by differences in work history: differences in state-specific rules cause Black claimants to have an 8.4% lower replacement rate than white

[2]Note that unlike Bohren, Hull, and Imas (2022), our objective is not to decompose the racial gap into a part that is coming from discrimination, and one that is not. In particular, we don't assume that the gap unexplained by work history fully reflects discrimination, nor that the gap explained by work history reflects no discrimination.

claimants. We find no residual racial gap once we account for state rules and work history differences. When we analyze separately the gap in eligibility (extensive margin) and the gap in the replacement rate of eligible claimants (intensive margin), we find that differences in state rules generate racial inequality at both margins. Our results hence highlight that differences in UI rules generate gaps in entitlements between Black and white claimants. Additionally, we reproduce our analysis for monetary rules only: in that case, we perfectly observe all the relevant work history variables, so concerns about omitting some aspects of work history are minimal. This analysis confirms that differences in state rules generate racial inequality, and shows that differences in monetary rules alone generate a 4.8% racial gap in replacement rate.

These findings explain the sources of racial inequality in UI entitlements among UI claimants. However, if the claimant population is selected in specific ways, this inequality could differ from the inequality in UI entitlements among all unemployed workers. For example, if Black unemployed workers are relatively more likely to claim in stringent states, our estimates would overstate the influence of state rules on racial inequality in UI entitlements among unemployed workers. To address this concern, we compare the population of newly unemployed workers in the Current Population Survey (CPS) and the population of claimants in the BAM data. We find that the two populations are similar in the dimensions that matter to quantify the role of state rule differences. In particular, the share of Black claimants and the share of Black unemployed workers are not systematically different in states with stringent rules.[3] This implies that, Black unemployed workers are not relatively more likely to claim in stringent states than White unemployed workers.[4] We then simulate the racial gap in UI entitlements—i.e. the UI that workers would receive if they claimed—explained by state rule differences among unemployed workers, based on the CPS statistics: we find that it is similar to the one we estimated in the population of claimants. Overall, these analyses show that the selection into claiming does not amplify the role of state rules differences. We conclude that differences in state rules generate racial inequality in UI entitlements for all unemployed workers, not just for those who claim UI.

After showing that state rule differences create racial inequality in UI, we tackle our second main research question: are these differences between states efficient? In each state, the efficient level of UI generosity is the one that a race-neutral central planner would choose, based on local economic factors. Our analysis here follows the same logic as outcome tests for discrimination (e.g., Rose (2021), Hull (2022), Mogstad, Canay, and Mountjoy

[3]Note that what matters for the role of state rules is whether Black workers tend to claim more than white workers systematically *in stringent states*. In contrast, whether Black workers tend to claim more than white workers on average *in all states* is not directly relevant for our research question.

[4]This pattern is not in contradiction with the finding in Anderson and Meyer (1997) that unemployed workers are more likely to claim when UI benefits are higher. In particular, this pattern is about the racial difference in the propensity to claim, not the overall propensity to claim. We find that the relative propensity to claim of Black and white unemployed is similar in states with more stringent rules, but both groups could claim more or less in these states. We discuss this further in Section 5.4.

(2022)), which assess whether an individual (or an institution) who treats race groups differently actually maximizes her apparent race-neutral objective. Like with outcome tests, we can abstract from the question of *why* there is unequal treatment: showing that the unequal treatment is inefficient is enough to justify policy change, whether or not the unequal treatment is motivated by racist preferences.[5] To assess efficiency, we follow the literature on optimal unemployment insurance (Schmieder and von Wachter, 2016b) and measure the marginal welfare effect of an increase in unemployment insurance benefits. We calculate these marginal effects *state by state* and then analyze their correlation with the racial composition of the state.

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, we find that the marginal welfare effect of increasing the level of unemployment benefits is unambiguously higher in states with a higher share of Black claimants. Our conclusions are unchanged when we use alternative calibrations. They are actually strengthened when we allow the unemployment duration elasticity to vary by state: when we estimate this elasticity in the BAM data, we find that it is smaller in states with a higher share of Black claimants in the state. Therefore, the behavioral cost of increasing UI generosity is even lower in those states, when we use these state-varying elasticities. Overall, we conclude that the differences across states in unemployment insurance rules generate racial gaps that cannot be justified by economic efficiency, the apparent race-neutral objective of the unemployment insurance system.

Overall, our results imply that more harmonized UI rules across states could both reduce racial inequality in the rights to unemployment benefits, and increase the efficiency of the UI system. State rule differences might not be the only source of racial inequality in unemployment insurance: for instance, discrimination could lead to Black workers having a worse work history before job loss, feeling discouraged from claiming for UI, or having their former employers dispute their claims more often. However, by showing the contribution of one factor that is directly under the control of policy makers, our study provides policy pathways to reduce racial inequality in UI. We finally discuss the effect of various reforms harmonizing UI rules across states. Our simulations suggest 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 paper makes several contributions. First, it relates to recent analyses of racial inequality coming from the design of institutions. Racial biases in U.S. institutions are likely widespread, as many key social programs were created during a time of historically high racism (Lieberman (2001a), Katznelson (2006)). For instance, occupational exclusions from

[5] If the unequal treatment does come from racist preferences, it is necessarily inefficient, as a racist decision maker "must act as if he were willing to pay something" (Becker, 1957).

the federal minimum wage voted in 1938 importantly contributed to the racial wage gap until the 1960s (Derenoncourt and Montialoux, 2021). While economists might have underappreciated the role of institutions in the past due to the focus on individual discrimination (Small and Pager (2020)), a recent literature shows that biases in institutions have a great impact on racial inequality (e.g., Derenoncourt and Montialoux (2021),Aaronson, Hartley, and Mazumder (2021), Rose (2021)).[6] Our paper adds to this literature by focusing on the level of decentralization: states have the autonomy to set the rules in many key social programs in the U.S. (e.g., UI, the Temporary Assistance for Needy Families, Medicaid) and have chosen increasingly diverging rules in recent decades (Grumbach, 2022).[7] We show that UI decentralization penalizes Black people, without maximizing the policy objective of UI.

Second, we contribute to a literature on racial inequality in the access to unemployment insurance. Two types of prior descriptive evidence suggested that state rule differences might be associated with racial inequality. A strand of studies documented state-level correlations between the size of the Black population and the strictness in some dimensions of UI rules (e.g, O'Leary, Spriggs, and Wandner (2022a)). Our contribution is to systematically account for all dimensions of the rules and for the UI-relevant work history of Black and white individuals. Another strand of articles described racial gaps in UI receipt, using individual survey data (Nichols and Simms (2012),Gould-Werth and Shaefer (2012), Kuka and Stuart (2021)). In particular, Kuka and Stuart (2021) analyze the contribution of various factors (e.g., state UI rules, demographics, work history, local economic conditions) to the racial gap in the UI received by unemployed workers, using a Kitagawa-Oaxaca-Blinder decomposition. The authors explain that their decomposition must be interpreted in a *statistical* sense rather than in a *causal* sense: the UI received by unemployed workers captures both their UI entitlement and their claiming behavior—which can depend on unobservable variables. We complement the work by Kuka and Stuart (2021) in two ways. First, we focus on the *UI entitlements*, rather than analyzing the UI *received*. This allows us to credibly include in our decomposition all the relevant explanatory factors and identify their *causal* effect on the racial gap in UI entitlements. Second, using the BAM data helps us avoid key concerns about the measurement of UI receipt and work history variables in surveys (Meyer, Mok, and Sullivan (2015),Larrimore, Mortenson, and Splinter (2022b,a)). Since rules on UI entitlements are directly under the control of policy makers, it is key for the policy debate to show with the best possible causal evidence that the design of the rules leads to racial inequality without increasing efficiency.

Third, we contribute to the welfare analyses of UI. We calculate the welfare effect of a marginal increase in UI generosity following the sufficient statistics approach (Baily

[6] Aaronson, Hartley, and Mazumder (2021) studies the "redlining" maps produced by the HOLC federal organization in the 1930s ; Rose (2021) studies rules for convicted offenders on probation.

[7] Differences across states rules might create racial inequality in the TANF historically and today (Lieberman (2001a) Parolin (2021)), and in Medicaid (Michener (2018)).

(1978a), Chetty (2006), Schmieder and von Watcher (2016)). We provide the first evidence of differences across states in how far from optimal the UI rules are. Our approach is related to the recent studies of UI generosity over the business cycle (Kroft and Notowidigdo (2016a), Schmieder, von Wachter, and Bender. (2012)): the authors measure the marginal welfare effects of increasing UI in different periods (instead of different states), and analyze the correlation with business cycle measures (instead of share of Black claimants).

The paper is organized as follows. Section 2 presents the institutional context and the BAM data. Section 3 describes our empirical strategy. Section 4 presents new descriptive statistics about UI claims. In section 5, we estimate the contribution of state rules differences to the racial gap in unemployment insurance. The welfare analysis in Section 6 tests whether the degree of disparities across state rules is efficient. Section 7 discusses various additional considerations. Section 8 concludes.

2 Institutional context and data

2.1 Unemployment insurance in the U.S.

In the U.S., workers who lose their jobs can apply for unemployment benefits by filing an initial claim. After the initial eligibility has been determined, claimants must file continuing claims every one or two weeks to keep receiving unemployment benefits. We focus on the outcome of the initial claim in this paper. The eligibility and Weekly Benefit Amounts of initial claimants depend on two types of determinations: monetary and non-monetary (USDOL, 2019). The specific rules for these determinations vary across states.

The federal-state system The unemployment insurance system, established by the Social Security Act of 1935, leaves a great deal of autonomy to the States: within federal guidelines, state legislatures can determine benefit amounts, duration, and eligibility requirements (Baicker, Goldin, and Katz, 2007). Proponents of a fully national program at the time feared that states with a large proportion of Black workers might use this autonomy to exclude Black workers.[8] And in many ways, the Unemployment Insurance system indeed failed to properly include Black workers in the following decades. Many States excluded from unemployment insurance agricultural and domestic occupations—in

[8]For instance, Charles Houston of the NAACP testified in Congress: "May I call attention to the unemployment-insurance provisions? As to that, we call the committee's attention to the fact that the definition of those who are to benefit under the unemployment-insurance provision is left up to the respective States. Now, where the Negro population is in the majority, or in largest numbers, you have the Negroes in occupations which, either under workmen's compensation acts or any other sort of legislation or other economic-insurance protection, are excluded from the benefits of the act. In these States, where your Negro population is the heaviest, you will find the majority of Negroes engaged either in farming or else in domestic service, so that, unless we have some provisions which will expressly extend the provisions of the bill to include domestic servants and agricultural workers, I submit that the bill is inadequate on the unemployment-compensation provision."

which Black workers are over-represented—until Congress extended the federal tax to agricultural and domestic workers in 1976, or even after (e.g. Texas waited until 1985). States also imposed increasingly strict eligibility criteria in terms of time-worked or wage-earned. Unemployment Insurance was thus a "moving target" for the population of Black workers increasingly shifting into the covered industrial sector (Lieberman (2001b), Katznelson (2006)). Today, there are no longer occupational exclusions, but many aspects of UI rules appear to differ widely from state to state, based on the "Comparison of State UI Laws" published each year by the Department of Labor. As the rules are complex and multi-dimensional, it is difficult to quantify the differences in generosity from these documents. We will provide details on the general principles common to all states in the next paragraphs, and then provide novel descriptive statistics about the amount of cross-states disparities in UI generosity taking advantage of the richness of the data we use.

Monetary determinations Monetary variables are both used to determine "monetary" eligibility and to compute the Weekly Benefit amount. First, monetary variables are used to test if claimants meet "monetary" eligibility criteria, meant to ensure a certain level of labor force attachment. Most 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 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: claimants' employment duration during the base period must exceed a certain number of weeks in New Jersey, Ohio, Oregon, and Pennsylvania, or a certain number of hours in Washington.

Besides, monetary variables are also used to compute Weekly Benefit Amount. The measure of earnings used to the compute the Weekly Benefits Amount varies across states: some states use the earnings received during part or all of the base period, while other states use the weekly wage earned in the weeks worked during the base period. Ultimately, the Weekly Benefit Amount generally corresponds to about 50% of the prior weekly wage, but states impose caps on Weekly Benefit Amounts. This means that eligible claimants with high prior wages 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 both importantly reduce the effective replacement rates and generate progressivity in the UI received by eligible claimants. States also have a statutory minimum Weekly Benefit Amount, which increases the benefit amount for eligible claimants with low earnings. In practice, these minima do not importantly affect the amount of WBA received, as they are binding for very few UI recipients.

Non-monetary determinations Non-monetary variables are also considered to assess claimants' eligibility. Most importantly, 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. However, individuals with a voluntary separation can be considered eligible in some states if the separation is considered in good cause, such as to relocate because of a spouse's employment. Additionally, other non-monetary eligibility criteria require that the claimant is able and available to work. In practice, this last type of criteria is mostly binding 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.

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.[9] Since 1987, all states have been required by the DOL to conduct weekly audits on paid claims, i.e., to investigate the status of UI recipients. In 2001, this was extended to include denied claims, i.e., to investigate the status of claimants who received a disqualifying determination. We start using denied claims in 2002 as relatively few audits were conducted in 2001. The claims to be audited are selected following a pre-defined random sampling procedure: they are selected randomly within each state, calendar week, and claim type (the four types are: paid, monetary denials, separation denials, and other denials). Paid claims are sampled from all benefit payments in 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. First, they systematically ask claimants to fill a standardized questionnaire to collect information on their demographic characteristics, their prior job and their search activities. They can collect complementary information through employer interviews, third-party verification, income verification, etc.

2.3 Construction of the representative sample of claimants

We use data on paid and denied audited claims from the Benefit Accuracy Measurement (BAM) (Woodbury, 2002; Woodbury and Vroman, 2000) for the years 2002-2017. These audit data cover both new claimants (i.e. claimants who are applying to start receiving

[9] 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`.

UI) and continuing claimants (i.e. those who have already started to receive UI). We focus on new claimants to avoid the over-representation of workers with long unemployment duration. To construct a dataset representative of *new claimants*, we combine the audited paid and denied claims and implement a couple of sample restrictions. The most important one is that we restrict the sample of paid claims to the first compensated week, and we restrict the sample of denied claims to the initial eligibility denial.[10] This leads to a sample of about 195,000 new claims: about 23,000 paid new claims 172,000 denied new claims. To make inference on the full population of new claimants, we use weights equal to the inverse of the probability that a new claim is included in our study sample. See Appendix A.1 for more details.

To validate our data construction, we compute from our study dataset the count of all new claims, paid new claims, denied new claims and compare them to the closest statistics available. We use the Department of Labor's Table ETA 5159: this table contains comparable aggregate statistics at the quarter and state level.[11] First, it contains information on the count of new filed claims, which we can compare to the count of new claimants in BAM (though the DOL measure includes people who filed a claim and left unemployment right after before getting any determination and the BAM measure does not). Second, the DOL Table contains information on the count of first payments, which should be close to the count of new paid claimants in BAM. Finally, though the DOL Table does not include a count of denied new claimants, we can approximate it by taking the difference between the count of new claims and of paid new claims, like in O'Leary and Wandner (2020). Overall, despite the small differences in the statistics definitions, we see that all our BAM-derived measures and the aggregate DOL measures align very closely in Figure A.1—which provides a good validation of our data construction. We also compare the composition of paid claimants in the BAM sample to that of continuing claimants, available in the Department of Labor's (also aggregated) ETA 203 report ("Characteristics of the Insured Unemployed") in Table A.1. Again, the two sources align very closely.

2.4 Information on claimants

Non UI-relevant characteristics The BAM data includes rich information on the characteristics of claimants. First, the BAM data contains a set of demographic characteristics (including race and ethnicity) collected for statistical purposes that are a priori not relevant for UI determinations. This information is self-reported in a standardized questionnaire that all claimants fill during the audit. Claimants have to report their race category (white, Black or African American, Asian, American Indian or Alaska Native, Na-

[10]Note that this reduces the sample of paid claims more than it reduces the sample of denied claims, because a larger fraction of denials happen at the start of the spell.

[11]The DOL Table ETA 5159 and the BAM data are generated independently and using very different procedures. For the BAM sample, states must produce weekly a list of claims (the UI transactions files), which is cleaned by a federal program, and among which claims to be audited are then randomly selected.

tive Hawaiian or Other Pacific, Islander, Multiple Categories Reported, Race Unknown) and separately report their ethnicity (Hispanic, Not Hispanic, Unknown).[12] 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. The BAM data also contains very rich information on the past labor market experience of all claimants that is not used for UI determinations: weekly wage in last job, prior occupation, prior industry.

UI-relevant work history Second, the BAM data are unique in that they contain the precise Work History variables that are used by UI officers, for monetary and non-monetary determinations (as described in Section 2.1). The monetary work history variables are measured based on states' quarterly wage records and include the Base Period Earnings, the Highest Quarter Earnings in base period, the ratio of the Highest Quarter Earnings over all Base Period Earnings, and the Weeks Worked in base period. We convert all monetary variables in 2019 dollars using the CPI downloaded from FRED. The work history variable that is relevant for separation determinations is the Reason for separation from prior employers, and it is determined by UI officers from claimants' and employers' declarations. However, there are two data limitations. First, for denied claims, we only observe the work history variables that correspond to their type of denial. Therefore, we only observe monetary work history variables for claimants who were paid or monetary-denied, and we only observe separation reasons for the claimants who were paid or separation-denied. Second, not all states use the same set of variables for their monetary determinations, and we only observe the monetary variables that are used to determine UI rights in the state at that time. Fortunately, most states use the same set of monetary variables (90% of monetary determinations in our data): the Base Period Earnings and Highest Quarter Earnings.

Therefore, in some parts of our analysis, we focus on the specific outcomes and subsamples that are unaffected by these data limitations: we study racial gaps in the outcomes of monetary determinations in the 90% of state-years that use the standard set of monetary variables. In other parts of the analysis, we study racial gaps in the most general outcomes and for the full sample of claimants, by using proxies for the incomplete work history variables. We are in a great position to construct such proxies, as we observe the work history variables in part of our sample, together with a rich set of (non-UI relevant) individual characteristics. In particular, we observe prior wages for all claimants, which are very correlated with the monetary variables that are used for UI determinations. This allows us to predict work history variables to address these data limitations. For more details, see Appendix A.2.

[12]Note that demographic information is also collected by UI officers in some states, independent of the audit process. The Department of Labor uses this second source of information to issue statistics on claim counts by demographics (ETA 203 "Characteristics of the Insured Unemployed" reports).

Unemployment insurance outcomes Finally, the BAM data contains information on UI receipt, namely eligibility and the Weekly Benefit Amount. 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.[13] 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 the 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 Empirical strategy

Our objective is to identify where the gap in UI entitlements between Black and white claimants in the U.S. comes from. In this section, we first formally define the different components of the racial gap, then explain our empirical method to estimate them.

3.1 Decomposition of the racial gap in UI

The state-specific UI rules parameters According to UI rules, UI outcomes are a function of work history variables in each state. The determination of UI outcomes in each state k can hence been described by the following model:

$$\mathbb{E}(Y|S_k = 1, X, \mathbb{1}_{g=b}) = \alpha_{0,k} + \alpha_{1,k} \cdot X + \beta_k \mathbb{1}_{g=b} \tag{1}$$

where Y represents the UI outcome of claimants, S_k is an indicator that claimants live in state k and X denotes claimants' work history characteristics. $\mathbb{1}_{g=b}$ is a dummy variable equal to 1 when claimants are Black, and zero when they are white. The α coefficients capture the rules in each state: they describe the state-specific baseline level of UI outcome for white claimants ($\alpha_{0,k}$) and the premium on UI outcome associated with work history variables ($\alpha_{1,k}$). The UI rules are supposed to be the same for everyone in a given state, and therefore independent of race. But in practice, UI outcomes could be affected by race through direct discrimination. This is why we allow for the outcomes of Black claimants to differ from that of white claimants in the same state and with the same work history. This is captured by the state-specific coefficient β_k.

Our approach to measure UI rules parameters is complementary to the approach in previous studies that code UI rules using the public documentation provided by the De-

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

partment of Labor (e.g., Gruber (1997), Chetty (2008), Kuka (2020)). Coding in detail all the rules relevant for our study (about the computation of replacement rates and monetary and non-monetary eligibility) is complex and necessarily imperfect, as the relevant parameters go beyond what is reported in the main DOL tables. Our data-driven approach allows us to determine the rules in the maximum level of detail that is useful to reconstruct claimants' UI entitlements using the BAM data, with no discretion. It is hence best suited for the purpose of our study.

The components of the racial gap in UI To assess the contribution of state rule differences to racial gaps in UI outcomes, we need to compare the current situation with a counterfactual one where rules would be set at the same benchmark level in all states. We set this benchmark at the average of the rules across states (where states are weighted by their claimant population size). We represent the parameters of the average UI rules by $\overline{\alpha}_0 = \sum_k \frac{N_k}{N} \cdot \alpha_{0,k}$, 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 the overall number of claimants. We also define the coefficients $\widetilde{\alpha}_{0,k} = \alpha_{0,k} - \overline{\alpha}_0$ and $\widetilde{\alpha}_{1,k} = \alpha_{1,k} - \overline{\alpha}_1$ which capture how the rule in state k departs from the average rule. When these coefficients 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 be defined as follows (we provide details in Appendix B):

$$\Delta = \underbrace{\sum_k \left[\widetilde{\alpha}_{0,k} \cdot \Big(\mathbb{P}_b(S_k=1) - \mathbb{P}_w(S_k=1)\Big) + \widetilde{\alpha}_{1,k} \cdot \Big(\mathbb{E}_b(X|S_k=1)\mathbb{P}_b(S_k=1) - \mathbb{E}_w(X|S_k=1)\mathbb{P}_w(S_k=1)\Big)\right]}_{\text{Gap explained by state rule differences}}$$
$$+ \underbrace{\overline{\alpha}_1 \cdot \Big(\mathbb{E}_b(X) - \mathbb{E}_w(X)\Big)}_{\text{Gap explained by work history differences}} + \underbrace{\sum_k \beta_k \mathbb{P}_b(S_k=1)}_{\text{Unexplained gap}} \tag{2}$$

To simplify notations, we add the subscript b (resp. w) to the expectation or probability symbol to indicate it is conditional on claimant being in race group b (resp. w): e.g., $\mathbb{E}_b(Y) \equiv \mathbb{E}(Y|\mathbb{1}_{g=b} = 1)$ or $\mathbb{P}_b(S_k=1) \equiv \mathbb{P}(S_k=1|\mathbb{1}_{g=b} = 1)$.

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 UI rules in all states. This gap would be eliminated if UI rules were the same across states. The second component is the gap explained by differences in the work history variables of Black and white claimants at the national level. It captures the part of the racial gap in unemployment benefits that would exist due to racial differences in work history, if all claimants were exposed to the same rule, which we defined as the average of state rules.

Finally, the third component is the gap unexplained by work history variables and state rules. 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:

$$(\widetilde{\alpha}_{0,k}+\widetilde{\alpha}_{1,k}\cdot\mathbb{E}_b(X|S_k=1))\Big(\mathbb{P}_b(S_k=1)-\mathbb{P}_w(S_k=1)\Big)+\widetilde{\alpha}_{1,k}\mathbb{P}_w(S_k=1)\cdot\Big(\mathbb{E}_b(X|S_k=1)-\mathbb{E}_w(X|S_k=1)\Big) \tag{3}$$

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 ($\widetilde{\alpha}_{0,k}+\widetilde{\alpha}_{1,k}\cdot\mathbb{E}_b(X|S_k=1)$ is negative) in states where Black claimants are over-represented ($\mathbb{P}_b(S_k=1)-\mathbb{P}_w(S_k=1)$ is positive). Second, Black claimants are disadvantaged when the premium on work history characteristics is larger ($\widetilde{\alpha}_{1,k}$ is positive) in states where their average work history characteristics is particularly far below that of white claimants ($\mathbb{E}_b(X|S_k=1)-\mathbb{E}_w(X|S_k=1)$ 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.

3.2 Estimation of the components of the racial gap in UI

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 The decomposition of the gap in model (1) is estimated as:

$$\hat{\Delta}=\sum_k\Big(\hat{\tilde{\alpha}}_{0,k}\cdot(\overline{S_{k,b}}-\overline{S_{k,w}})+\hat{\tilde{\alpha}}_{1,k}\cdot(\overline{S_{k,b}}\cdot\overline{X_{k,b}}-\overline{S_{k,w}}\cdot\overline{X_{k,w}})\Big)+\hat{\alpha}_1\cdot(\overline{X_b}-\overline{X_w})+\sum_k\hat{\beta}_k\overline{S_{k,b}} \tag{4}$$

where $\overline{X_g}$ 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.

To estimate the components of the racial gap, we hence proceed in two steps. First, we measure the rule parameters $\hat{\alpha}_{0,k}$ and $\hat{\alpha}_{1,k}$ by estimating model (1) 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, we compute the various components of the gap based on the estimates of the state rule parameters $\hat{\alpha}_{0,k}$ and $\hat{\alpha}_{1,k}$ and various sample averages: we compute $\sum_k \left(\hat{\hat{\alpha}}_{0,k} \cdot (\overline{S_{k,b}} - \overline{S_{k,w}}) + \hat{\hat{\alpha}}_{1,k} \cdot (\overline{S_{k,b}} \cdot \overline{X_{k,b}} - \overline{S_{k,w}} \cdot \overline{X_{k,w}})\right)$ to estimate the gap explained by state rule differences; we compute $\hat{\hat{\alpha}}_1 \cdot (\overline{X_b} - \overline{X_w})$ to estimate the gap explained by work history differences; we estimate the residual gap by taking the difference between the raw gap in average UI outcomes and the two other components. To account for the estimation of the rule parameters in the first step and for sample variation, we use bootstrap to compute the standard errors of our estimates of 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. By construction, we use two different samples for these analyses: we include all claimants for the analyses including the extensive margin, while we focus on eligible claimants when we analyze the intensive margin. We face different limitations in these two samples (see Section 2.4 for more details). We hence use different proxies for work history variables in these two different samples, to always exploit the richest information available in the sample considered.

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. This correspond to the situation of Black claimants before the non-monetary determinations are made, and would correspond to their final outcome if there were no non-monetary eligibility criteria.[14] 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).[15]

Identification assumption Our core causal estimands give the Black-white gap in UI outcomes driven by (i) work history and by (ii) state laws. Component (i) captures what the gap would be if Black and white work histories were identical. Component (ii) captures what the gap would be if Black and white claimants were distributed equally across states. Since, in theory, nothing else goes into the calculation of benefits, our models should uncover the causal effects of these factors—assuming we do not omit relevant work history information 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 provide evidence that our identifying assumptions are credible, we implement a series of robustness checks. We start with testing the sensitivity of our results to our use of proxies for work history variables. In the analysis where we observe all relevant work history variables, we successively estimate the components of the racial gap using the actual work history variables, or the two types of proxies, and show that our results remain stable. Then, 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 in each state. We systematically find that our estimates of the components of the racial gap remain very similar to our main results. We review all robustness checks in details in Section 5.3.

[14]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 weight correction.

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

4 Descriptive statistics

4.1 Descriptive statistics on UI claimants

Who are UI claimants? In Table 1, we present the characteristics of all new claimants in column (1)—both those who end up being paid UI and those who end up being denied UI—and of new paid claimants in column (2), based on our BAM dataset. For comparison, we then present the characteristics of newly unemployed workers from the monthly CPS excluding new entrants in the labor force, in column (3). Columns (1)-(3) hence describe various *inflows* of workers into unemployment. Additionally, columns (4) and (5) describe the corresponding stocks of workers: the workers who receive UI and those who are unemployed for any duration.

The statistics presented in Table 1 yield interesting findings. First, Black individuals represent 19% of all UI claimants, while white individuals represent 70% (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 paid claimants (column (2)), indicating above average rejection rates for Black claimants. In the CPS, we see that Black people represent 16% of new unemployed people (column (3)), which is similar to their proportion among new recipients and slightly below their proportion among new claimants. However, in the stock (col (4) and (5)), the fraction of Black people among UI recipients (17%) is smaller than among all unemployed workers (20%). These statistics indicate that Black people spend a larger share of their unemployment spell with no insurance, but that this is because they stay unemployed longer, not because they start receiving UI less frequently. It might seem surprising that the claiming rates implied by these comparisons appear higher for Black workers, and that the recipiency rates appear close for Black and White newly unemployed workers. It is at odds with evidence of lower claiming and recipiency rates for Black workers in survey data (Lovell (2002), Nichols and Simms (2012), Gould-Werth and Shaefer (2012), Kuka and Stuart (2021)), but is consistent with other studies based on administrative data (O'Leary, Spriggs, and Wandner, 2022a).[16] One possible explanation is that the amount of misreporting in survey data might vary by race (Meyer, Mok, and Sullivan, 2015; Larrimore, Mortenson, and Splinter, 2022b,a). Given these discrepancies across data sources, more research is needed to provide reliable measures of the claiming or recipiency rates by race. Importantly, the conclusions of our paper do *not* depend these differences claiming or recipiency rates by race. In Section 5.4, we will compare the racial gaps in the rights to UI for the population of BAM new claimants and for the population of CPS new unemployed. This exercise does *not* rely on count of Black and White people in these populations, it only relies on information of their

[16] The statistics provided by (O'Leary, Spriggs, and Wandner, 2022a) correspond to our analysis of the stock in columns (4) and (5). The small discrepancies likely come from the fact that their data (ETA 203) does not cover all States, as shown in Table A.1.

composition—which is easier to compare across data sources.

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 benefits rights. 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 to claiming is only a 29% replacement rate, vs. around 36% for a white claimant. This is driven by the large gap in eligibility rates: 76% of white claimants are considered eligible for benefits while only 61% of Black claimants are. This is similar to the statistics obtained from the CPS Non-Filer Supplement, where 71% of white and 64% of Black applicants received UI (Gould-Werth and Shaefer, 2012). 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 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, which tends to decrease their replacement rates. We note that this is consistent with prior evidence that Black and white workers experience the same relative income drop upon unemployment, conditional on receiving unemployment benefits (Ganong et al., 2021).

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.

4.2 Descriptive statistics on differences in UI rules across states

While there is indirect evidence that states with a larger Black population might have less generous UI rules (e.g., O'Leary, Spriggs, and Wandner (2022a)), there was no comprehensive measure of state generosity to directly test this. Using our empirical strategy, we build an Index of UI generosity in each state that summarizes all the dimensions of UI rules, and that does not depend on the composition of the population in that state. This is defined as the average statutory Weekly Benefit Amount that all U.S. claimants would get if the rules of the state were implemented in all the U.S. Using the notation detailed in Section 3.1, this Index for state k can be expressed as: $\hat{\alpha}_{0,k} + \hat{\alpha}_{1,k} \cdot \overline{X}$. We provide further statistics on these measures of UI generosity, and on others, in Appendix Table D.1. The Index ranges from \$92 in Ohio to \$319 in Rhode Island (bottom row).

Our comprehensive Index of UI generosity allows us to test the correlation between UI generosity and the share of Black claimants. In Figure 2, Panel (1) shows a clear negative correlation between the share of Black claimants and the Index of generosity of state UI rules, weighting states by their number of claimants. The typical Weekly Benefit Amount decreases by \$9 for every 10 percentage points increase in the share of Black claimants. This figure hence confirms that the share of Black claimants is negatively correlated with all the dimensions of UI generosity. 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 D.1). The other Panels in Figure 2 focus on specific aspects of UI generosity instead: the cap on weekly benefits (relative to the mean prior wage of claimants in the state) in Panel (2)[17]; the minimum level of base period earnings required for eligibility (relative to the mean prior wage of claimants in the state), in Panel (3) ; the rate at which states grant eligibility to claimants who quit their prior job, in Panel (4). In all cases, states tend to be more generous when they have fewer Black claimants. All these dimensions hence contribute to the negative correlation between UI generosity overall and the share of Black claimants.

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 D.2. We build an Index of state premium on work history, similar to our Index of state generosity. We successively measure the racial gap in work history in each state, using various work history characteristics, such as the gap in base period earnings. Overall, it appears from all panels in Figure D.2 that states tend to give a larger premium for work history when Black claimants have a worse work history than white claimants. This should amplify the gap in unemployment insurance generated by differences in state rules.

5 Do state rule differences create racial inequality?

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.

[17] This is consistent with Figure 1: The Figure also indicates that there is a negative correlation between the size of the Black population and UI generosity, as far as the cap on WBA is concerned. But unlike Figure 2, we don't weight states by their number of claimants in this exercise.

5.1 Racial inequality 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 the rules prevailing in the state where the claimant lives, differences in individual work history (applying the same average UI rules to all claimants), and unexplained differences. The bottom panel of the table reports the gaps, relative to the white mean for that outcome (in %).

The raw Black-white gap On average, Black claimants receive a $92.3 lower Weekly Benefit Amount (WBA) than white claimants (Table 3, first line in column (1)). This is 33.6% 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 6.5 percentage points lower, corresponding to a 18.3% 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 Table 2). Still, the 18.3% 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 18.8% less likely than white claimants to be found eligible, which corresponds to a 14.2 percentage points lower eligibility rate (column (3), bottom and top panels). When they are eligible, Black claimants receive 18.2% lower benefits, which represents a $66.4 gap (column (4), bottom and top panels). 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 hence receive lower WBA 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 discuss the gap explained by state rule differences: component (i). The estimates imply that, due only to state rules differences, Black claimants receive 11.2% (or $30.7) less in benefits (column (1)), and receive an 8.4% (or 3 percentage points) lower replacement rate than white claimants (column (2)). These estimates of the gaps explained by state rule differences carry our key findings. Black claimants receive a substantially 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 18.3% raw gap in replacement rate and the 8.4% gap caused by state rules in suggests that roughly half of the raw racial gap in replacement rate is due to institutional factors.

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 3.6% 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 gap through both the extensive and the intensive margin of UI.

The gap explained by work history We next discuss the gap explained by work history differences: component (ii). Due to different work history, Black workers get 23.6% ($ 64.7) 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: 10.2% (3.6 percentage points; column (2)). This is because work history variables 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 11.9% 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 4.2% 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 (4.2% 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 the gap 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: this is 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. Addressing racial inequality in unemployment insurance would therefore require a reform of the institution towards more harmonization of state rules, rather than more monitoring of UI officers' behavior.

5.2 Racial inequality in monetary determinations

After analyzing the determinants of the gap in UI generosity overall, we now focus on monetary determinations. This analysis has two objectives. First, we want to check if the qualitative patterns documented in Table 3 hold in a sample where we can more precisely measure the relevant work history variables. Indeed, 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., in the state-months that use the same set of variables for monetary eligibility—see Section 3.2 for more details). Second, we want to assess how much of the overall gap in outcomes documented in Table 3 might come from monetary determinations alone. This is an important question as the literature so far has focused on monetary determinations: most papers study the amount benefits that UI recipients are entitled to, which is entirely determined by monetary determinations; and among the few articles that analyze eligibility criteria, most focus on monetary requirements (Leung and O'Leary (2020), de Souza and Luduvice (2020), Chao (2022)). By construction, the racial gaps and its components at the intensive margin (documented in columns (4) and (5) of Table 3) must entirely come from monetary determinations. However, both monetary and non-monetary determinations contribute to eligibility decisions, so it is an open question how much monetary factors alone might contribute to the racial gap at the extensive margin (column (3) of Table 3), and therefore to the overall racial gap (columns (1)-(2) of Table 3).

The results are presented in Table 4, following the same format as Table 3. The first line of columns (1)-(2) shows that Black claimants are disadvantaged in monetary determinations, just like they are overall. In monetary determinations, Black claimants get 24.2% lower weekly benefits (i.e., $73.65 less), and a 8.1% lower replacement rate (i.e., 3.3 percentage points less) than white claimants. Importantly, we see that state rule differences play an important role (Component (i), columns (1)-(2)): they generate a 4.5% gap in weekly benefits (i.e., $13.61), and a 4.8% gap in replacement rate (i.e., 1.9 ppt). Overall, the components of the racial gaps in monetary determinations are hence qualitatively similar to those in all determinations (Table 3): differences in state rules generate gaps between Black and white claimants with the same work history in the outcomes from monetary determinations alone. This reinforces the conclusion from our analysis of all determinations.

Going into further details, we can notice that the gaps caused by monetary determinations are similar in sign, but smaller in magnitude than the overall gaps for all components in columns (1)-(3). In particular, the gap in replacement rate explained by state rules (component (i)) amounts to 4.8% in Table 4, and 8.4% in Table 3. This indicates that both differences in monetary factors and non-monetary factors contribute to the gap explained by state rules: Black workers are both exposed to monetary and non-monetary rules that are less advantageous to them in their states. However, as expected, gaps are virtually identical in Table 4 and Table 3 at the intensive margin, where only monetary factors matter (columns (4)-(5)). The small differences only come from the fact that we exclude states that use a non-standard set of monetary work history variables in Table 4, and only include actual work history variables instead of proxies (we discuss robustness checks that isolate the role of proxies in the next Section).

5.3 Robustness checks

In this section, we present various evidence of the robustness of our decomposition results. First, we test the sensitivity of results to our use of proxies for work history variables. We use proxies when we analyze the outcomes from all types of determinations because the relevant work history variables are missing for some claimants (Table 3). In contrast, we do not use proxies when we analyze the outcomes from monetary determination only, because we observe all the relevant variables in that case (Table 4). In our robustness check Table D.2, we focus on the analysis of the outcomes of monetary determinations, and evaluate if our results are sensitive to using proxies instead of the fully observed actual work history variables relevant for monetary determinations. Whether we use the actual work history variables, or the two types of proxies, we obtain very similar estimates. This suggests that our results for other outcomes are robust to the use of proxies.

Second, we show that our decomposition results remain unchanged when we vary the approach for estimating the UI rule coefficients in model (1). First, we control for additional claimants' characteristics that should not be relevant for UI outcomes (gender, age, education level). If we had omitted important information correlated with race in model (1), adding these characteristics could change our results. We show in Table D.3 that results do not change. In Table D.4, we then show that we also obtain the same decomposition results when we allow the state-specific UI rule parameters to change over time. Therefore, the simplifying assumption that state rule parameters stay constant during our study period does not appear to bias our results.

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 (1), but machine learning models may better capture the non-linearities. 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 include paid claimants audited later in their spells in addition to new claimants. Using a Random Forest method also gives us the flexibility to add year as a predictor, and hence allow us to 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 D.5 the estimated components of the racial gap using the predictions from the Random Forests model. The estimates closely align with those in Table 3.

Additionally, we estimate the contribution of work history differences to the racial gap, using the standard Kitagawa (1955)-Oaxaca (1973)-Blinder (1973) decomposition, where we measure how much of the racial gaps in UI can be explained by work history. The Kitagawa-Oaxaca-Blinder decomposition allows coefficients on work history to differ by race, while our main decomposition allows these coefficients to differ by state. The gap explained by work history that we obtain in the Kitagawa-Oaxaca-Blinder decomposition should be similar to the one that we obtain in our main decomposition. The gap unexplained by work history in the Kitagawa-Oaxaca-Blinder decomposition is comparable to the sum of the gap explained by state rules and of the residual gap in our main decomposition. Reassuringly, we find in Table D.6 that the estimated racial gaps in UI explained by work history are very close in the Kitagawa-Oaxaca-Blinder decomposition and in our decomposition.

Finally, we consider in Table D.7 the gaps between Black or Hispanic and non-Hispanic white claimants (instead of Black vs white claimants). We find that the gaps explained by state rule differences are qualitatively similar for all UI outcomes to those obtained in our main analysis, but a bit attenuated.

5.4 Racial inequality in UI entitlements, among *all* unemployed

We have shown how state rule differences affect the racial gap in UI received by UI claimants. We now check that the effects of state rule differences on racial inequality among claimants generalize to the population of newly unemployed workers. A key concern is that Blacks with unfavorable work histories may be disproportionately claiming in stingy states, which would lead us to overestimate the impact of differences in state rules on UI entitlements among the unemployed. Here, we extend our analysis to all unemployed workers, including those who don't claim UI: we investigate the sources of inequality in *entitlements for UI* among unemployed workers, i.e. in the UI that they would receive if they claimed. We collect state-level information on newly unemployed workers in two data sources: we count the number of Black and white newly unemployed workers in each state using the monthly CPS (like in Table 1, column (3)), and we measure their average base period earnings using the Annual Social and Economic Supplement (ASEC) of the CPS. As discussed in Section 3.1, the UI gap from state rules could arise out of (1) Black claimants living in less generous states and (2) higher racial wage gaps in states which put a greater premium on work history. We thus compare the newly unemployed with the new claimants from our

BAM data to see if the correlations between (1) race and generosity, and (2) racial wage gap and the work history premium, are the same across the two samples.

In Figure D.3 Panel (1), we present in red the correlation of state generosity with the fraction of Black claimants (just like in Figure 2). We present in blue the correlation with the fraction of Black newly unemployed workers from the CPS. Black individuals are similarly over-represented in stringent UI states among claimants and among all unemployed. In other words, Black claimants are over-represented in stringent states not because Black unemployed workers claim more in those states, but they tend to live in those states. Note that this pattern is not in contradiction with the finding in Anderson and Meyer (1997) that unemployed workers are more likely to claim when they can receive a higher benefit level, if eligible. First, this pattern is about the racial difference in the propensity to claim, not the overall propensity to claim. We find that the relative propensity to claim of Black and white unemployed is similar in states with more stringent rules, but both groups could claim more or less in these states. Second, this pattern is about correlation, not causality: we find the strictness of states UI rules does not correlate with the relative propensity to claim for Black people. States with stricter UI rules can differ from other states in several ways, that could influence the propensity to claim in opposite directions. For instance, unemployed workers in stricter states might be less likely to claim because they have less to gain if they are eligible, but more likely to claim because they have less savings to self-insure.

Panel (2) presents the correlation of state generosity with the state racial gaps in prior wages among claimants (just like in Figure D.2), and among unemployed workers. We see that the prior earnings of Black individuals tend to be less far below those of white people in states with a lower premium on work history, both among claimants and among all unemployed. In other words, Black claimant's earnings are closer to white claimant's earnings in the states with a low premium on work history, not because of selection into claiming, but because unemployed workers have smaller earnings gaps in those states.

Together, the panels in Figure D.3 suggest that the racial gap explained by state rule differences among unemployed workers is similar to the one we estimated among claimants. As a final step, we directly quantify the size of the racial gap explained by state rule differences among unemployed workers that is implied by these statistics. To do this, we modify the sample of BAM claimants by rescaling the size of the population and the average base period earnings in each race group and each state to match the corresponding statistics for the CPS newly unemployed workers. We then apply our decomposition method to this simulated population of unemployed. The results are presented in Table D.8: the estimates of the racial gap caused by state rule differences in the full population of unemployed are similar to our estimates for the population of claimants (comparing columns (3) and (4) to columns (1) and (2)). In sum, our evidence suggests that the population of claimants and of unemployed workers are similar enough that the racial gap in UI entitlements explained by state rule differences in the two populations is comparable.

6 Are state rule differences efficient?

After showing that differences UI generosity across states generate racial inequality, a key question is whether they represent an efficient response to differences in local economic conditions. If that is the case, there could be a trade-off between efficiency and racial equality.

6.1 Our approach to assess efficiency

We test if state rule differences—which create racial inequality—appear to increase efficiency. Our approach is comparable to outcome tests, widely used in the discrimination literature (e.g., Rose (2021), Hull (2022), Mogstad, Canay, and Mountjoy (2022)). After showing that an individual (or an institution) treats Black and white people differently, a key question is whether this might maximize her apparent race-neutral objective. These tests require specifying which outcome the individual wants to maximize based on the institutional context. One can then compare the outcome obtained under racial inequality with the outcome that could have been obtained without racial inequality. This test hence does not require explaining the behavior generating inequality, and in particular to determine whether it comes from racist preferences. We follow the same logic. But in our case, the maximization problem of the UI administration cannot be summarized with a single outcome. Instead, we lean on the sufficient statistics literature, which provides a model for the optimization problem for the UI central planner, and an empirical method to measure how far UI systems are in reality from the optimum (Baily, 1978b; Chetty, 2006). In this framework, the economic factors that are relevant to evaluate efficiency can be summarized by a set of key statistics related to state-level unemployment, UI benefits and taxes, the behavioral response to benefits increase and the income drop at job loss. We measure how far each state is from the maximum welfare that the race-neutral state central planner would have achieved. If states with a larger Black population are at a level of generosity further below the social optimum, then the lower generosity in those states both generates inequality and inefficiency.

6.2 Results from the efficiency analysis

The marginal welfare effect corresponds to the social value from increasing UI (from consumption smoothing) minus the behavioral costs (from increased unemployment). In practice, we use the formula provided by Schmieder and von Wachter (2016a) to measure, for each state, the welfare effects from increasing the transfers to the unemployed by $1 (see Appendix C.1 for more details). We measure the relevant statistics from various data sources (see Appendix C.2 for more details).

Marginal cost of a UI increase, state by state We first assess the marginal cost of a $1 increase in benefits state by state. Results are presented in Panel (1) of Figure 3. We find that the marginal costs decrease with the share of Black claimants in the state. We now explain how we measure the different components of this cost, and how each component varies across states with the share of Black claimants.

The marginal cost of a UI increase comes from the unemployed workers' behavioral response to unemployment benefits: their unemployment duration increases when benefits increase. But the magnitude of the cost associated with this behavioral response depends on various factors. Most importantly, it depends on the magnitude of the increase in *paid benefits duration* associated with an increase in *unemployment duration*. Indeed, an increase in unemployment duration *after* benefits exhaustion does not lead to additional benefits paid. We find that in states with a larger fraction of Black claimants, the exit rate out of unemployment is lower (Figure D.4 Panel (1)), and the maximum potential benefits duration is shorter (Figure D.4 Panel (2)). It follows that a larger fraction of workers stay unemployed *after* the maximum benefit duration. Therefore, an increase in unemployment duration has more limited consequences on the duration of paid benefits in states with a higher share of Black claimants (Figure D.4 Panel (3)).

To assess the marginal cost, we then measure the elasticity of unemployment duration. While there are many estimates for this elasticity for the U.S., there are no state-level estimates for all of the U.S. Therefore, we first assume that the elasticity is constant across states. We 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). Although assuming that the duration elasticity is the same across states might miss important aspects of this welfare calculation, this 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 study differences in 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. To estimate the elasticity using the BAM data, we regress the log of weeks of paid benefits on the log of the Weekly Benefits Amount, controlling for state fixed effects interacted with Base Period Earnings and Highest Quarter Earnings and a wide range of individual characteristics. The variation in the weekly benefits used for identification comes from non-linearities in the benefits formula in each state. Results are presented in Table D.9. Our results suggest that the elasticity of unemployment duration w.r.t weekly benefits amount is around 0.1-0.2 on average (col (1)). We find that this elasticity significantly *decreases* with the share of Black claimants in the state (col (2) and (3)). Using this calibration, the marginal welfare costs of UI increases are hence even lower in states with a high share of Black claimants.

Overall, we find that the different components of the marginal cost all tend to be lower in states with a high share of Black claimants, which is why we conclude that the marginal cost overall is lower in these states. The result presented in Panel (1) of Figure 3 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 D.9 would further accentuate the negative correlation.

Marginal social value of a UI increase, state by state Second, we assess the marginal social value of a \$1 increase in benefits state by state. Results are presented in Panel (2) of Figure 3. We find that the marginal social value increases with the share of Black claimants in the state. We now explain how we obtain this result.

The marginal social value of an increase in benefits comes from consumption smoothing. It can be measured using the drop in income associated with job loss 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 monthly panel from the Survey of Income and Program Participation (SIPP) to measure within individual drops in household income at job loss. We find that people experience a drop in their household income by about 18% at job loss, and that this drop in income is larger in states with a large Black population (Figure D.4 Panel (6)). 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 *level* 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 literature finds that the consumption of Black workers drops *more* than that of white workers facing a similar income shock (Ganong et al., 2021), the drop in 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 hence find that the marginal social value of a \$1 increase in benefits increases with the share of Black claimants, as presented in Panel (2) of Figure 3. In this Figure, we use the standard value 2 for the coefficient of risk aversion.

Marginal welfare effect of a UI increase, state by state From our results on the marginal costs (Panel (1), Figure 3) and the marginal social value (Panel (2), Figure 3), it follows unambiguously that there is 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 calibration of specific parameters. Appendix Figure D.5 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. The differences in state rules hence generate racial inequality, while being inefficient.

Why might states choose suboptimal levels of UI? In practice, there might be many obstacles preventing rules from being set at the social optimum. There might be inertia in how new rules get adopted when the economic environment changes. Some groups might have more influence in the political process, such that the rules maximize the welfare of only a fraction of the population. People might not have race-neutral preferences, unlike the social maximizer that we consider in our welfare analysis. Instead, people might have in-group preferences, i.e. put a higher weight on the welfare of people from their racial group.[18] Overall, many factors could contribute to the differences in generosity between states, and our analysis is not designed to identify them. However, our analysis does offer an evaluation of these differences and highlights potential policy changes: whether or not the current design reflects racist preferences, policies that reduce the differences in UI generosity across states could both reduce racial inequality and increase the efficiency of the UI system.

7 Discussion

Our results indicate that the differences in state rules that have emerged due to the decentralized structure of UI both generate racial inequity and inefficiency. In this section, we suggest some concrete policies that could reduce the differences in state rules, and finally discuss other potential sources of inequality in unemployment insurance.

7.1 The role of specific Unemployment Insurance rules

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 harmonizing some key policy parameters across states. Indirectly, this analysis helps highlight which dimensions of the current system contribute the most to the existing racial inequality. Note that in the rest of the paper, we have taken a very comprehensive and data-driven approach to define policy parameters (α). The drawback is that these policy

[18] Such in-group preferences are consistent with the findings in Alesina, Baqir, and Easterly (1999a), Luttmer (2001), Dahlberg, Edmark, and Lundqvist (2012), Feigenberg and Miller (2021)

parameters are difficult to relate to the policy debate. Here, we take a complementary approach: we focus on a few policy parameters that are very salient in the policy debate.[19]

Harmonization of specific UI rules For each policy parameter, we simulate an harmonization scenario where we align all states to the level of the most generous state in our study sample. We simulate the racial gap in replacement rate, assuming that the composition of claimants remains unchanged. We present the results in Figure 4. In each panel, the dark blue bar is the simulated gap explained by state rules, and the light blue part of the bar is the simulated gap explained by work history. In Panel (1), we see that harmonizing the maximum WBA alone would already decrease the gap in replacement rate explained by state rules from 8.4% to 6.6%. However, while the gap explained by state rules would decline with WBA harmonization, the total Black-white gap would actually increase from 18.3% to above 20%. This is because white claimants tend to have higher prior earnings, and hence benefit more from a higher cap on WBA.

We then consider two types of harmonization of eligibility requirements. First, we assume that all states only use Base Period Earnings to determine monetary eligibility, and set the level of earnings required at the minimum observed in our sample, hence aligning this eligibility criterion to the most generous state. We see in Panel (2) that harmonizing the earnings requirement in that way would decrease the gap induced by state rule differences from 8.4% to 7.5%, while also reducing the overall gap in replacement rate to 15.6% instead of 18.3%. Second, we harmonize the separation eligibility rules for claimants who quit their previous jobs.[20] When we align the treatment of quitters to the most generous state, the gap explained by state rule differences is reduced to 6.3%, and the overall gap is reduced to 14.7% (Panel (3)). Finally, Panel (4) shows that harmonizing simultaneously these three policy parameters would reduce the racial gap explained by state differences by about half, to 4.3% (and the overall gap to 14.7%). The difference across states in these three policy parameters—that are salient in the policy debate—does play a major role in generating racial inequality.

Finally, we consider intermediary harmonization scenarios, where we gradually set the federal minimum at various quartiles of the distribution of the parameter in our study dataset in Figure D.6.

Specific UI rules and racial gaps across the prior wage distribution The results in Figure 4 suggest that different reforms affect people in different parts of the prior earnings distribution. To explore this further, we analyze the gap in the average replacement rate for claimants at different quintiles of the distribution of prior hourly wages in Figure D.7. First, we see that existing state rule differences cause a large racial gap for claimants in

[19] See for instance Bivens et al. (2021), Dube (2021).

[20] 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.

all prior wage quintiles (Panel (0)). The racial gap is larger at the top of the prior wage distribution, where it ranges above 10%. We then examine the distribution of this gap under each hypothetical policy reform. Harmonizing the cap on WBA mostly decreases the racial gap explained by state rule differences for the two highest prior wage quintiles. In contrast, harmonizing eligibility requirements reduces the racial gap more at the bottom of the prior wage distribution. Overall, among the harmonization reforms we consider, adjusting upward the eligibility requirements appears to be the best suited to improve the situation of poor Black claimants. This finding is interesting in the light of the recent literature finding positive welfare effects of relaxing UI eligibility requirements Leung and O'Leary (2020).

7.2 Other sources of inequality?

Do state rule differences cause gaps across demographics other than race? We have emphasized the racial gaps in UI arising from differences in rules across states. But such differences could in theory generate gaps between any groups. In Figure D.8, 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 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 D.9: 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.

Racial bias in the measurement of work history variables? We have so far treated work history variables as given. But there might be room for subjectivity in the measurement of these variables. In that case, UI officers might discriminate against some claimants or might be tougher in certain states, which could generate racial bias in the measurement of work history, within states or across states. To test for such racial bias, we analyze the mistakes in the measurement of work history variables by UI officers that are detected by BAM auditors: to the extent that BAM auditors are less racially biased than state UI officers, systematic mistakes that disfavor Black claimants could be suggestive evidence of racial discrimination in the measurement of work history variables. We regress indicators of mistakes on claimants' characteristics in Poisson models, and report the incidence-rate ratios estimates in Table D.10.[21] We successively consider mistakes in the measurement of monetary variables (upper table), and separation variables (lower table). First, we see that these mistakes by UI officers are rare: 3.8% of white claimants have a mistake in their monetary variables, and 0.6% of white claimants have one in their separation reason. In the measurement of monetary variables, we then see that the prevalence of mistakes is not significantly different for Black and white claimants, in any of the specification considered. In contrast, Black claimants are 70-84% more likely to have mistakes in the assessment of the separation reason (columns (1)-(3)). But we find that Black claimants are both more likely to receive a favorable mistake in their separation reason (columns (4)-(6)), and a negative mistake (columns (7)-(9)). We note that these mistakes are very rare, so our estimates are imprecise. Overall, the pattern we uncover is not supportive of work history variables being measured in a way that disadvantages Black claimants. One possible explanation for the higher prevalence of mistakes in the measurement of separation reasons for Black claimants could be that employers appeal more often the reason for separation reported by Black claimants, which might make their claim more difficult to evaluate. Lachowska, Sorkin, and Woodbury indeed show that low-paying employers are more likely to report that the separation of their former employees was a quit rather than a layoff, and thereby dispute their claim for unemployment benefits.

8 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 18.3% Black-white gap in the replacement rate received by claimants: Black claimants receive a 29% replacement rate vs. 36% for white claimants. Using a Kitagawa-Oaxaca-Blinder style decomposition, we show that differences in state UI rules cause an 8.4% Black-white gap in the replacement rate. We further show that state differences would create a similar Black-white gap if all unemployed workers were to claim unemployment benefits. We thus show that differences in rules across states create racial inequality in the entitlement to UI. We then examine if the differences in rules across states are adapted 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. Therefore, our results imply that there is no equity-efficiency trade-off: by making UI rules more similar across states, policymakers could both increase Black-white equality *and* overall welfare.

Our findings highlight racial inequality during unemployment, which has important

[21] The coefficient associated with race cannot be interpreted causally, as claims might have unobserved characteristics that differentially expose them to mistakes. For instance, it could be that Black claimants tend to make claims that are more complicated to treat, which could create a correlation between the prevalence of mistakes and race even in the absence of discrimination.

consequences: 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 racial inequality. The UI system is not an isolated case: decentralization of 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)). And 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 (1999b)). Beyond decentralization, 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) in the justice system. Research shows that people tend to dislike redistributive 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.

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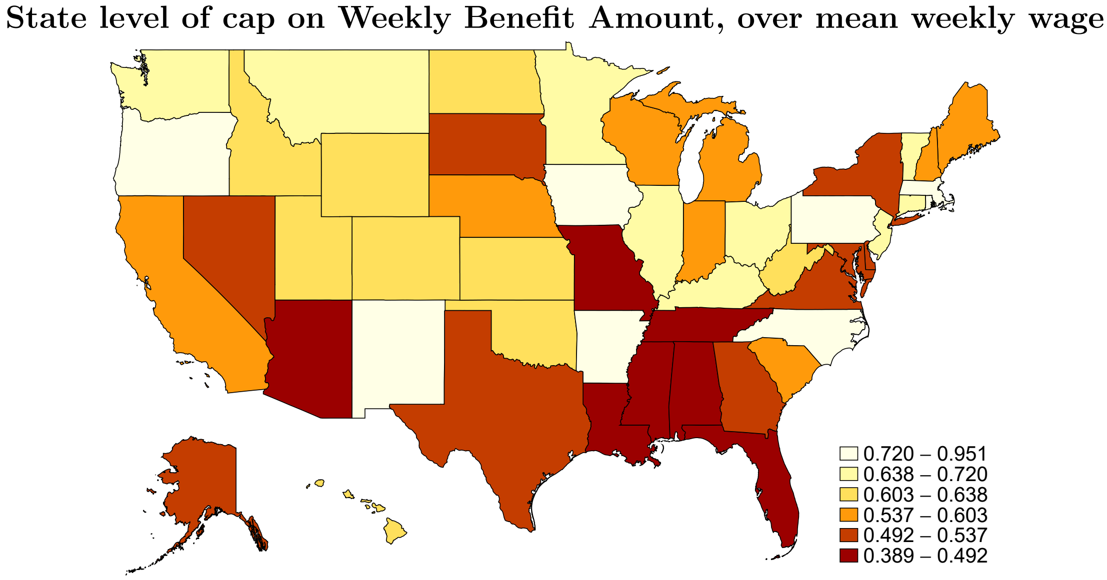
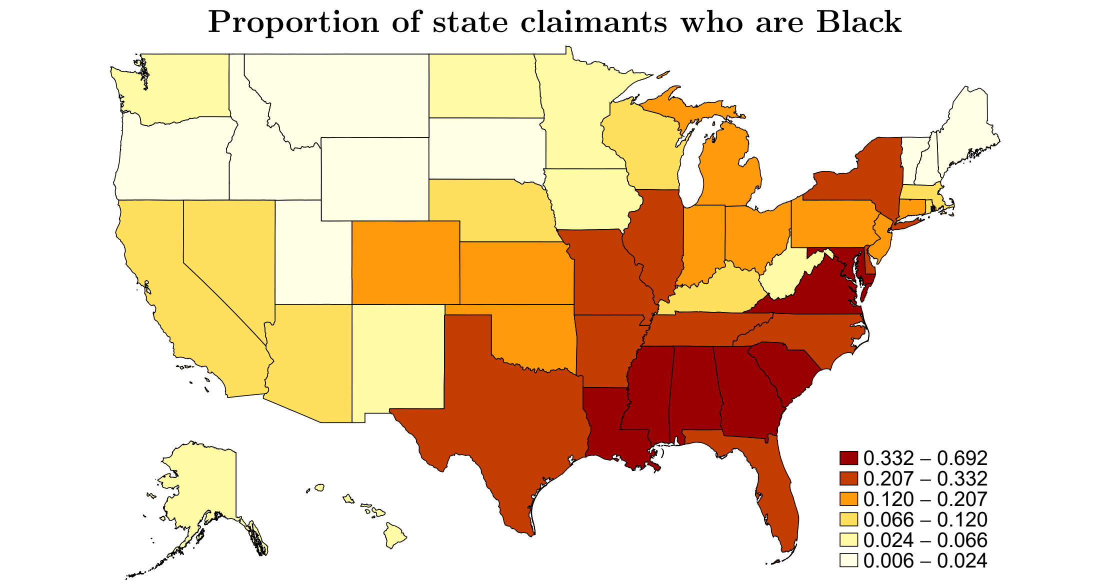
9 Tables and Figures

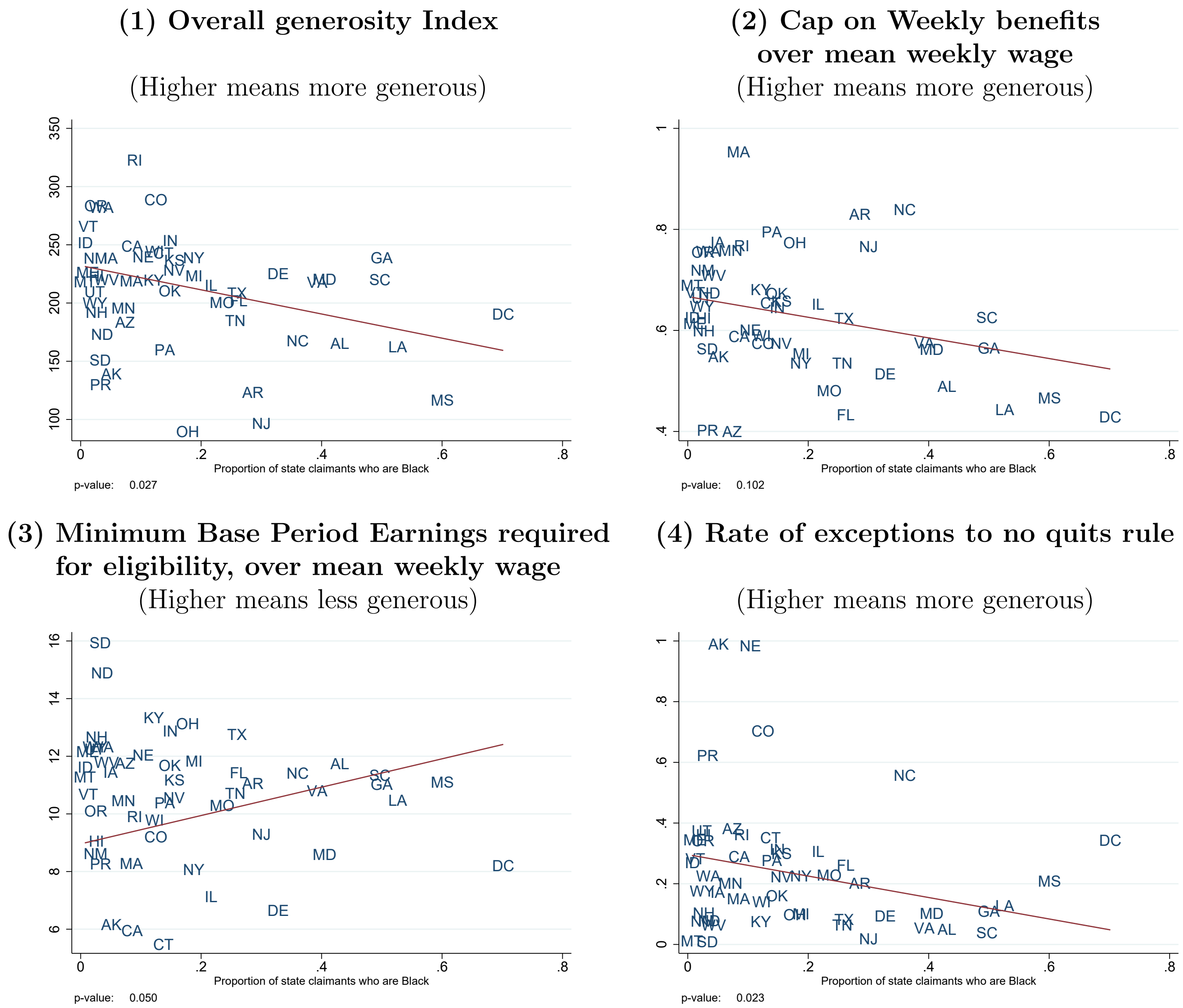
Figure 1: Cap on Weekly Benefit Amount and share of Black claimants





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.

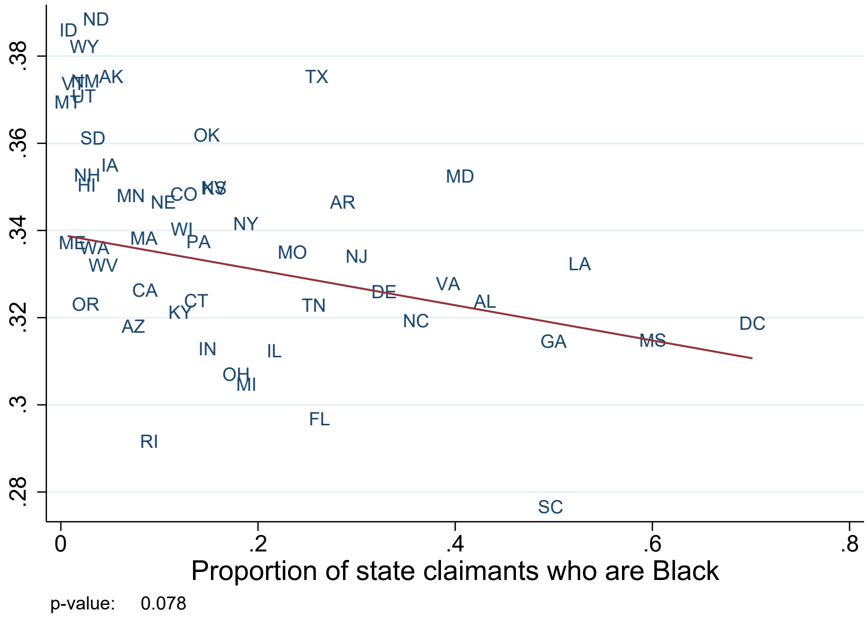
Figure 2: State rules and racial composition



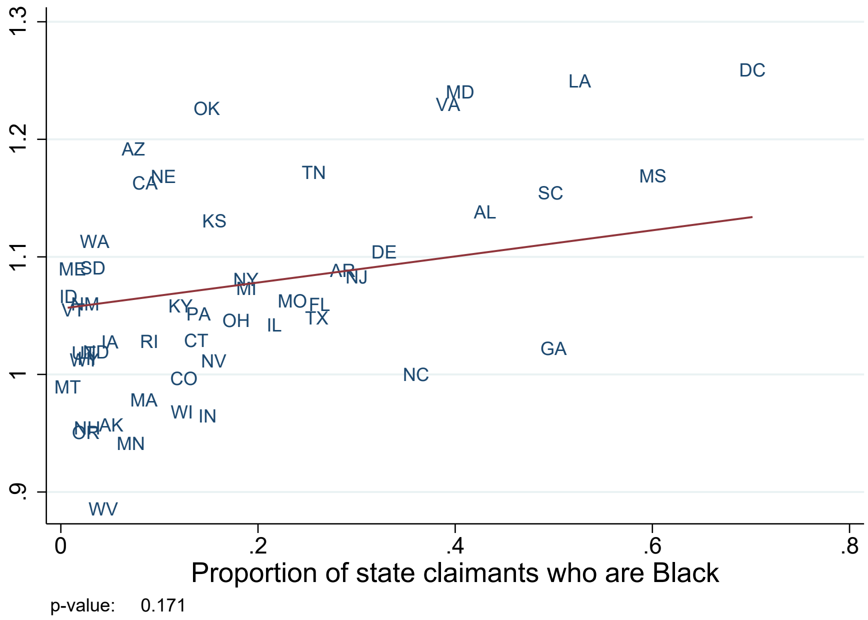
Notes: This Figure presents the correlation of state rule generosity and the share of claimants in the state who are Black. We measure state generosity using an Index summarizing all dimensions of state rules, in Panel (1) (see Section 4.2); the statutory maximum level of weekly benefits relative to the average prior wage in the state, in Panel (2) (like in Figure 1); the minimum Base Period Earnings level required for monetary eligibility relative to the average prior wage in the state, in Panel (3); the proportion of claimants quitting their jobs who are eligible, in Panel (4). 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) **Behavioral cost**

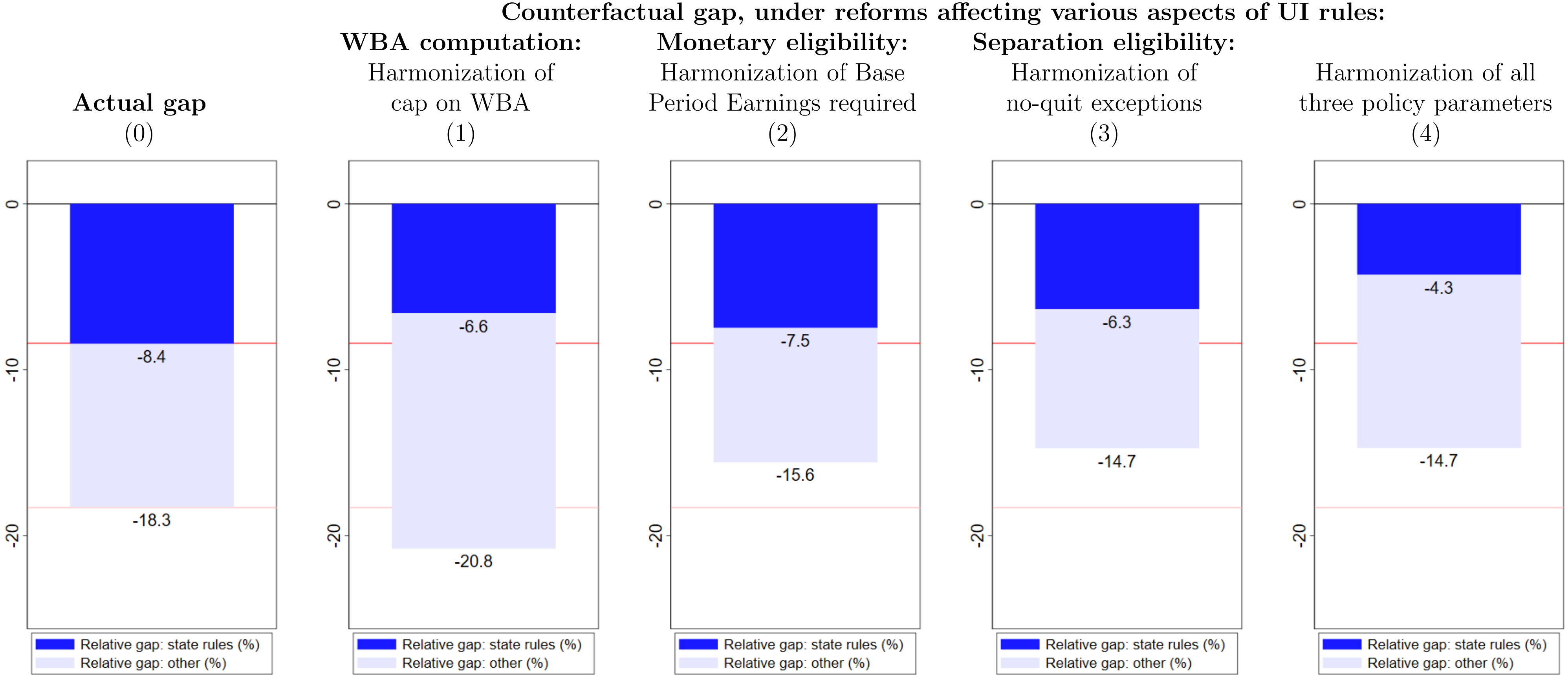


(1) **Social value**



Notes: This Figure shows the correlation across states between the proportion of UI claimants who are Black and various marginal welfare effects associated with a $1 transfer to unemployed workers. Panel (1) considers the marginal behavioral cost, Panel (2) considers the marginal social value. These terms are defined following the formula in Schmieder and von Wachter (2016a), and measured using the calibration presented in Table C.1 (more details are provided in Appendix C). We present the regression line and the corresponding p-value, obtained when each state is weighted by its number of claimants.

Figure 4: Racial gaps, under various hypothetical reforms of UI rules



Notes: We present the actual racial gap (in (0)), and the simulated racial gaps under various hypothetical policy reforms. We assume that all states align to the maximum level generosity in our study sample in terms of the cap on WBA (in (1)), the minimum BPE required for eligibility (in (2)), the rate of eligibility for job quitters (in (3)), or all of these three policy parameters (in (4)). The full horizontal bar represents the Black-white gap in replacement rate relative the mean replacement rate of white claimants (%), and the part in dark blue represents the Black-white gap explained by state rule differences relative the mean replacement rate of white claimants (%).

Table 1: Description of UI claimants, UI recipients, and unemployed workers

Variable	Flow			Stock	
	New claimants (BAM)	New paid claimants (BAM)	New unemployed (CPS)	All paid claimants (BAM)	All unemployed (CPS)
	(1)	(2)	(3)	(4)	(5)
Race					
White	0.70	0.73	0.76	0.72	0.72
Black	0.19	0.17	0.16	0.17	0.20
Asian	0.02	0.03	0.03	0.03	0.04
American Indian	0.01	0.01	0.02	0.01	0.01
Native Pacific Islander	0.00	0.00	0.00	0.01	0.00
Multiple races	0.01	0.01	0.02	0.01	0.02
Race Unknown	0.06	0.05	0.00	0.06	0.00
Ethnicity					
Hispanic	0.17	0.16	0.20	0.17	0.18
Non-Hispanic	0.80	0.80	0.80	0.79	0.82
Unknown	0.04	0.04	0.00	0.04	0.00
Gender					
Male	0.58	0.60	0.55	0.59	0.56
Female	0.42	0.40	0.45	0.41	0.44
Age					
<25	0.12	0.09	0.32	0.09	0.24
25-34	0.26	0.24	0.24	0.24	0.24
35-54	0.46	0.49	0.32	0.49	0.37
55+	0.16	0.17	0.12	0.18	0.15
Education					
Less than high school	0.14	0.14	0.20	0.14	0.17
High school	0.42	0.42	0.36	0.40	0.38
Some college	0.29	0.28	0.29	0.29	0.28
Bachelors or more	0.13	0.14	0.16	0.15	0.17
Observations	194,481	23,250	198,979	354,451	712,815

Notes: We provide descriptive statistics for the population of new UI claimants (col (1)) and new eligible UI claimants (col (2)), using our BAM study sample; and for the population of new unemployed workers excluding new-entrants (col (3)) using the CPS. In addition, we describe the stock of UI recipients in the BAM data (col (4)) and of unemployed workers in the CPS (col (5)). All data are for 2002-2017 in all U.S. states and the District of Columbia.

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

Variable	(1) All	(2) Black	(3) White	(4) Other
UI Outcomes				
Weekly benefit amount	251.47	182.37	274.66	227.22
	(199.31)	(177.22)	(199.91)	(201.26)
Weekly benefit amount, if eligible	350.34	297.31	363.66	341.24
	(143.90)	(130.50)	(143.34)	(148.10)
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				
Base period earnings (in thousands)	31.54	22.34	34.43	27.92
	(31.05)	(21.59)	(32.85)	(28.83)
Highest quarter earnings (in thousands)	10.81	7.82	11.74	9.80
	(9.69)	(6.55)	(10.37)	(8.38)
Highest quarter earnings, over base period earnings	0.43	0.46	0.42	0.48
	(2.80)	(0.22)	(0.19)	(8.56)
Weeks worked	34.44	29.11	36.42	24.49
	(18.12)	(19.31)	(17.06)	(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	0.10	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	194,481	44,090	124,778	25,613

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
	(3.297)	(0.004)	(0.006)	(3.670)	(0.005)
(i) Explained by State Rule differences	-30.724***	-0.030***	-0.068***	-13.023***	-0.014***
	(3.883)	(0.006)	(0.010)	(1.370)	(0.002)
(ii) Explained by Work History differences	-64.745***	-0.036***	-0.090***	-52.813***	0.020***
	(3.183)	(0.005)	(0.008)	(3.182)	(0.004)
(iii) Unexplained	3.159	0.001	0.016	-0.518	-0.003
	(4.108)	(0.008)	(0.012)	(1.572)	(0.003)
White mean	274.690	0.356	0.755	363.662	0.472
Gap relative to White mean (in %)	-33.6	-18.3	-18.8	-18.2	0.6
(i) relative to White mean (in %)	-11.2	-8.4	-9.0	-3.6	-3.0
(ii) relative to White mean (in %)	-23.6	-10.2	-11.9	-14.5	4.2
(iii) relative to White mean (in %)	1.2	0.3	2.1	-0.1	-0.6
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. We consider various UI outcomes in different columns: the Weekly Benefit Amount (in $ per week), the replacement rate (as a share), the eligibility status. The first line presents the size of the raw racial gap. The three lines below presents the size of the three components: (i) the gap explained by differences in state rules, (ii) the gap explained by racial differences in work history (iii) the unexplained gap (see section 3.1 for details). In the bottom part of the Table, we present these gaps relative to the mean UI outcome for white claimants, in %. We use the full sample of state-months and all claimants in col (1)-(3); in col (4)-(5) we only include eligible claimants. We use two sets of work history variables depending on the outcome considered, and two proxy methods which always use the richest information available in the considered sample (see section 3.2 for details). 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	-73.654***	-0.033***	-0.081***	-56.901***	0.006
	(3.739)	(0.005)	(0.005)	(3.782)	(0.005)
(i) Explained by State Rule differences	-13.605***	-0.019***	-0.026***	-10.738***	-0.012***
	(1.756)	(0.002)	(0.006)	(1.401)	(0.002)
(ii) Explained by Work History differences	-60.600***	-0.014***	-0.063***	-46.232***	0.019***
	(3.396)	(0.004)	(0.006)	(3.399)	(0.004)
(iii) Unexplained	0.551	0.001	0.008	0.069	-0.002
	(1.497)	(0.002)	(0.006)	(1.305)	(0.003)
White mean	304.345	0.405	0.872	348.863	0.464
Gap relative to White mean (in %)	-24.2	-8.1	-9.3	-16.3	1.3
(i) relative to White mean (in %)	-4.5	-4.8	-3.0	-3.1	-2.5
(ii) relative to White mean (in %)	-19.9	-3.5	-7.2	-13.3	4.2
(iii) relative to White mean (in %)	0.2	0.3	0.9	0.0	-0.4
N	81,393	81,393	81,393	18,075	18,075

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 racial gap. The three lines below presents the size of the three components: (i) the gap explained by differences in state rules, (ii) the gap explained by racial differences in work history (iii) the unexplained gap (see section 3.1 for details). In the bottom part of the Table, we present these gaps in relative terms, i.e. divided by the mean UI outcome for white claimants. We consider various UI outcomes in different columns: the Weekly Benefit Amount (in $ per week), the replacement rate (as a share), the eligibility status. In this Table, we restrict our sample to the 90% of monetary determinations in the state-months that use the standard set of monetary variables, for all claimants in col (1)-(3) and for eligible claimants only in col (4)-(5). Work history variables include: Base Period Earnings, Highest Quarter Earnings, Ratio of Highest Quarter Earnings over Base Period Earnings. We present in parentheses bootstrapped standard errors obtained using 1000 iterations.

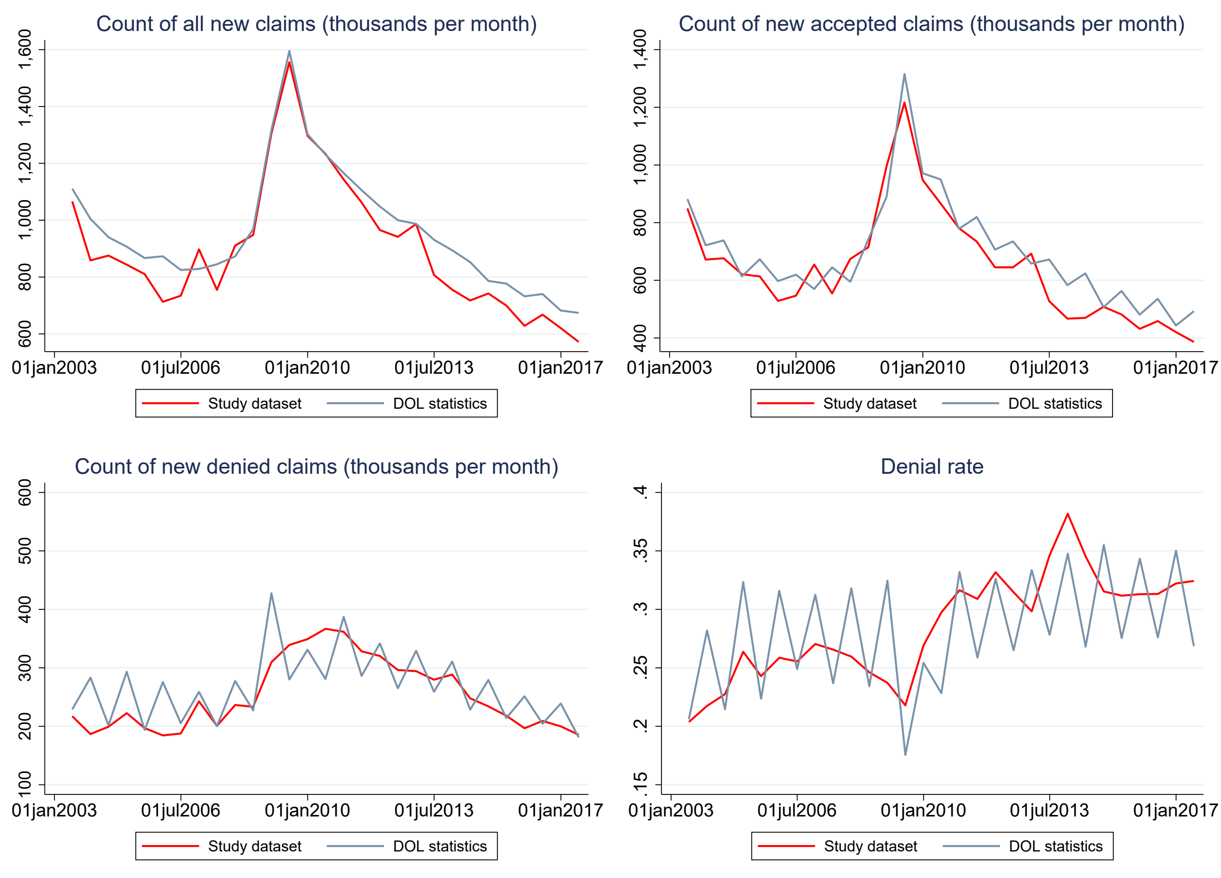
ONLINE APPENDIX

A Data construction

A.1 Construction of sample of new claims

In this study, we analyze the sample of new claims that received a BAM audit. To make our sample representative of all new claims, we use weights equal to the inverse of the probability that a new claim is included in our study sample. Because of the audit stratified random sampling procedure, the fraction of new claims in the population of all claims and the fraction of audited new claims in the population of audited claims should be equivalent. Therefore, the probability for new claims of being in our study sample simply corresponds to the probability for a claim to be audited, which is systematically reported in the BAM data.

Figure A.1: Validation checks:



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. Statistics for similar measures are available by quarter and state in the DOL table ETA 5159.

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.

The count of initial claims reported in Section A of ETA 5159 provides a measure of new claims. The count of first payments in Section B of ETA 5159 provides a measure of new paid claims. The difference of the two provides a measure of new denied claims. Finally, we compute the denial rate as initial claims minus first payments as a share of initial claims, like in O'Leary and Wandner (2020). We present the evolution of these measures Figure A.1. First, we see that the count of new claims measured in our study data is very close to the measure in the DOL statistics, and follows a very close evolution. The count of new accepted claims measured in our data matches almost perfectly the equivalent statistics from DOL. The count of denied claims in our data is also very close to the count reported to the DOL. Importantly, the denial rates measured in both data sources is very close, and move together.

We then compare the composition of paid claimants in the BAM sample to that of continuing claimants, available in the Department of Labor's ETA 203 report ("Characteristics of the Insured Unemployed").[22] The ETA 203 data provides counts of claimants within several demographic categories. Columns (1) and (2) 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 because several states do not ask for the race and ethnicity of all claimants (O'Leary, Spriggs, and Wandner, 2022a). 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.2 Two methods to proxy for work history variables, in samples with missing values

When we analyze 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 us to build proxies for the full sample of claimants, but based on less information. The second builds proxies for the subsample of eligible claimants, based on richer information. Each method helps us address a different data limitation.

First method – for all claimants For each denial type, the data only includes the work history variables necessary to determine the type of determination considered in the audit (either monetary or non-monetary). 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

[22]For a discussion on the methodology of the ETA 203, and a comparison with the CPS unemployed population, see O'Leary, Spriggs, and Wandner (2022b).

Earnings, Highest Quarter Earnings over Base Period Earnings and number of weeks worked during the base period. But the data contains for all claims a rich set of non-UI relevant variables, including the weekly wage earned in the last job. 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: prior wage ,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 estimate a model predicting the reason for separation based on all the variables available for all claims (the same as listed above), 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 gives us 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 samples 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 eligible claimants (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 Period Earnings are either considered alone or in combination with Weeks Worked. In the sample of eligible claimants, we estimate a model predicting 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 gives us 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 Period 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

Using the same notation as in Section 3.1, we can rewrite the UI outcome model (equation 1) as:

$$\mathbb{E}(Y|S_k = 1, X, \mathbb{1}_{g=b}) = \overline{\alpha}_0+\overline{\alpha}_1\cdot X+\widetilde{\alpha}_{0,k}+\widetilde{\alpha}_{1,k}\cdot X+\beta_k\cdot \mathbb{1}_{g=b} \tag{B.1}$$

One can interpret $\overline{\alpha}_0+\overline{\alpha}_1\cdot X$ as the UI outcome that a white claimant with characteristics X would obtain in the average state. $\widetilde{\alpha}_{0,k}+\widetilde{\alpha}_{1,k}\cdot X$ 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 work history X.

From the UI outcome model, we derive the expected UI outcome for people in one race group $g \in \{b, w\}$. To simplify notations, we add the subscript b (respectively w) to the expectation or probability symbol to indicate that it is an expectation or probability conditional on claimant being in race group b (respectively w): e.g., $\mathbb{E}_b(Y) \equiv \mathbb{E}(Y|\mathbb{1}_{g=b} = 1)$ or $\mathbb{P}_b(S_k=1) \equiv \mathbb{P}(S_k=1|\mathbb{1}_{g=b} = 1)$. We obtain the following expression, using the fact that states represent a partition of the full U.S. population:

$$\begin{aligned}
\mathbb{E}_g(Y) &= \sum_k \mathbb{P}_g(S_k=1)\cdot\mathbb{E}_g(Y|S_k=1)\\
&= \sum_k \mathbb{P}_g(S_k=1)\cdot\Big(\overline{\alpha}_0+\widetilde{\alpha}_{0,k}+(\overline{\alpha}_1+\widetilde{\alpha}_{1,k})\cdot\mathbb{E}_g(X|S_k=1)+\mathbb{1}_{g=b}\cdot\beta_k\Big)\\
&= \overline{\alpha}_0+\overline{\alpha}_1\cdot\mathbb{E}_g(X)+\sum_k \mathbb{P}_g(S_k=1)\cdot\Big(\widetilde{\alpha}_{0,k}+\widetilde{\alpha}_{1,k}\cdot\mathbb{E}_g(X|S_k = 1)+\mathbb{1}_{g=b}\cdot\beta_k\Big)
\end{aligned}$$

We then derive the gap between the expected UI outcomes of Black and white claimants $\Delta = \mathbb{E}_b(Y)-\mathbb{E}_w(Y)$:

$$\begin{aligned}
\Delta = &\sum_k \left(\widetilde{\alpha}_{0,k}\cdot\Big(\mathbb{P}_b(S_k=1)-\mathbb{P}_w(S_k=1)\Big)+\widetilde{\alpha}_{1,k}\cdot\Big(\mathbb{E}_b(X|S_k=1)\mathbb{P}_b(S_k=1)-\mathbb{E}_w(X|S_k=1)\mathbb{P}_w(S_k=1)\Big)\right)\\
&+\overline{\alpha}_1\cdot\Big(\mathbb{E}_b(X)-\mathbb{E}_w(X)\Big)+\sum_k \beta_k\mathbb{P}_b(S_k=1)
\end{aligned}$$

C Marginal welfare effect of UI, state by state

C.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:

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

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 a simpler expression, which is typically easier to measure. Assuming that the hazard of leaving unemployment is constant, and that D has Exponential(s) distribution, we can simplify the expression for the costs as follows (with S_P the share of unemployed workers who exhaust their benefits, and s the constant exit rate out of unemployment):

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

with $\xi \equiv 1-(1+sP)e^{-sP} = \frac{dB}{db}\frac{db}{dD}$

C.2 Calibration

Main statistics We approximate for each state the marginal welfare effects, using the aggregate statistics for 2008-2013 reported in Table C.1, Panel A. We combine data from the US Department of Labor, the CPS, and the SIPP:

- We use publicly available information on the total UI tax collected (USDOL-ETA, 2021a) over the number of employed workers in the CPS to measure τ
- We use publicly available information on the total amount of benefits distributed by each state each year (USDOL-ETA, 2021a) over the number of unemployed workers in the CPS to measure b
- We collect information on the maximum benefits duration (in weeks) for each state and each year from state UI laws to measure P (USDOL-ETA, 2021b)
- 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).
- We use the Survey of Income and Program Participation (SIPP), a panel containing information on monthly household earnings, to measure the drop in earnings at job loss. In particular, we use the dataset constructed from the SIPP in Rothstein and Valletta (2017) to study the drop in income during unemployment. We measure income after job loss by taking the average monthly household income during the non-employment spell restricted to when unemployment duration is under the normal potential benefit duration in the respondent's state.[23] We measure income before job loss by taking the average monthly income in the 2-4 months before job loss, as in Rothstein and Valletta (2017).

[23] This is based on `thtotinc` in the SIPP data and `yl` in the Rothstein and Valletta (2017) files.

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

	Mean	Min	Max	Std.Dev.
A/ Statistics from various sources				
Weekly transition from unemployment to employment (i.e. s)	0.07	0.05	0.12	0.01
Maximum potential benefits duration in weeks (i.e. P)	25.86	23.97	30.00	0.88
Inverse rate of unemployed with spell shorter than P (i.e. $\frac{1}{1-S\_p}$)	1.57	1.19	1.81	0.13
Ratio UI tax rate over UI replacement rate (i.e. $\frac{\tau}{b}$)	0.05	0.03	0.07	0.01
Relative drop in income at unemployment (i.e. $\frac{c\_e - c\_u, t \leq P}{c\_e}$)	0.17	-0.02	0.27	0.04
B/ Calibrated parameters				
Risk aversion coefficient (i.e. γ)	2.00	2.00	2.00	0.00
Elasticity of unemployment duration wrt benefits (i.e. η_D, b)	0.38	0.38	0.38	0.00
C/ Welfare calibration				
Social value calibration	0.33	-0.05	0.55	0.07
Behavioral cost calibration	0.33	0.28	0.39	0.02
Welfare effect calibration	-0.00	-0.38	0.23	0.08

Notes: This Table presents various statistics at the state level, where each state is weighted by its number of claimants.

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 tracks 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)). This 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. 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 D.5 (1)).

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 D.5 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. In Table D.9, 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.

C.3 Estimation of the elasticity of unemployment duration wrt UI level, using the BAM data on the audits of UI recipients

We don't observe the full duration of unemployment for BAM claimants, only the duration until the audit (let's denote it A). Since audits are conducted among a random sample of the stock people receiving UI, it is possible to back out the elasticity of unemployment duration with respect to benefits level ($\eta_{D,b}$)—which is economically meaningful—from the elasticity of the duration of paid benefits before an audit with respect to benefits level ($\eta_{A,b}$)—which we can estimate. Here, we explain how we obtain a formula relating $\eta_{A,b}$ to $\eta_{D,b}$, step by step.

Following Schmieder and von Wachter (2016a), we have assumed that D, the expected duration of unemployment, has Exponential(s) distribution, such that its density function $f(t) = se^{-st}$, the survival function $S(t) = e^{-st}$, and the expectation is $\mathbb{E}(D) = \frac{1}{s}$. We can see easily that under this assumption:

$$\mathbb{E}(B) = \int_0^P t \cdot s\mathrm{e}^{-st}\,dt + \mathrm{e}^{-sP}P = \frac{1-\mathrm{e}^{-sP}}{s}$$

Now, in our data, we observe the duration of unemployment at the time of the audit for a random sample of individuals in the stock of UI recipients, i.e. the population of people who have received UI at some point. The audit sampling is not a representative sample of people who start a UI spell (flow), it is representative of people receiving UI spell (stock): long UI spells are more likely to be sampled. Therefore, the probability to audit someone who will have a completed benefits duration around t, $P_A(B \in [t, t+dt])$, is not equal to the frequency of this completed benefits duration in the flow population, $P(B \in [t, t+dt])$. Instead, it is:

$$P_A(B \in [t, t+dt]) = \frac{tP(B \in [t, t+dt])}{\mathbb{E}(B)}$$

Besides, the average duration before the audit for someone who receives unemployment benefits for a duration t is $\frac{t}{2}$, given that the probability to be audited is constant over the time of the unemployment insurance spell.

$$\mathbb{E}(A) = \int_0^P P_A(B \in [t, t+dt])\frac{t}{2}dt = \int_0^P \frac{t^2 P(B = t)}{2\mathbb{E}(B)}dt = \frac{\mathbb{E}(B^2)}{2\,\mathbb{E}(B)}.$$

To derive an expression for $\mathbb{E}(A)$, we first compute $\mathbb{E}(B^2)$:

$$\mathbb{E}(B^2) = \int_0^P s\,t^2\,\mathrm{e}^{-st}\,dt + \mathrm{e}^{-sP}P^2 = \frac{2(1-(1+sP)\mathrm{e}^{-sP})}{s^2}\cdot$$

Therefore, we obtain:

$$\mathbb{E}(A) = \frac{1-(1+sP)\mathrm{e}^{-sP}}{s(1-\mathrm{e}^{-sP})} = \frac{1}{s} - \frac{P\mathrm{e}^{-sP}}{(1-\mathrm{e}^{-sP})}$$

Considering that s is a function of b, the derivative of $\mathbb{E}(A)$ wrt b gives:

$$\frac{d\mathbb{E}(A)}{db} = \frac{d\mathbb{E}(D)}{db}\cdot\left(1-\frac{s^2P^2\mathrm{e}^{sP}}{(1-\mathrm{e}^{sP})^2}\right)$$

And we have:

$$\eta_{A,b} = \eta_{D,b}\cdot\left(1-\frac{s^2P^2\mathrm{e}^{-sP}}{(1-\mathrm{e}^{-sP})^2}\right)\cdot\left(\frac{(1-\mathrm{e}^{-sP})}{1-(1+sP)\mathrm{e}^{-sP}}\right)$$

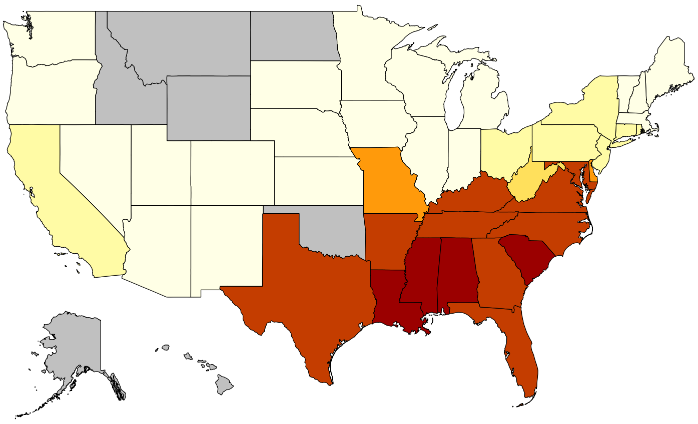
D Additional Tables and Figures

Table D.1: Description of state rules

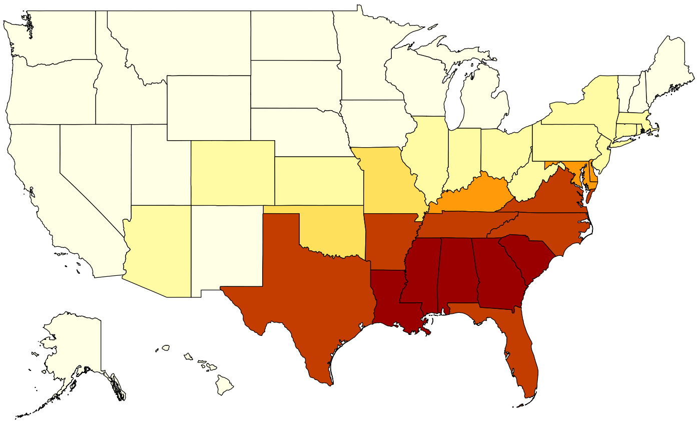
	Count	Mean	Min	p25	p50	p75	Max	Corr
Benefits amount, for those eligible								
Max WBA / Avg wage	52	0.63	0.40	0.56	0.59	0.70	0.97	-0.23
Prop recipents at Max WBA	52	0.31	0.00	0.22	0.32	0.40	0.68	0.30^{**}
Min WBA / Avg wage	52	0.09	0.01	0.06	0.08	0.09	0.20	-0.08
Prop recipents at Min WBA	52	0.00	0.00	0.00	0.00	0.00	0.11	-0.21
Benefits duration, for those eligible								
Max Duration	52	25.82	24.05	26.00	26.00	26.00	30.00	-0.42^{***}
Eligibility determination								
Min required BPE / Avg wage	52	9.98	5.55	8.12	10.48	11.84	16.05	0.27^{**}
Possibility of eligibility for job quitters	52	0.23	0.00	0.11	0.20	0.31	1.00	-0.31^{**}
Overall generosity								
Index of overall generosity	52	209.58	91.94	192.41	215.37	242.26	319.17	-0.32^{**}

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, over the state average weekly wage; the share of UI recipients at the maximum WBA; the statutory minimum level of benefits, over the state average weekly wage; the share of UI recipients at the minimum WBA; the maximum number of weeks people can claim UI in a spell; the lowest base period earnings required to be monetary eligible, over the state average weekly wage; the proportion of claimants quitting their jobs who are eligible; and an Index we build to summarize all dimensions of state rules generosity (see Section 4.2). 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 last column, we show the correlation between the UI rule parameter and the share of UI claimants who are Black, when each state is weighted by its number of claimants, with $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.10$.

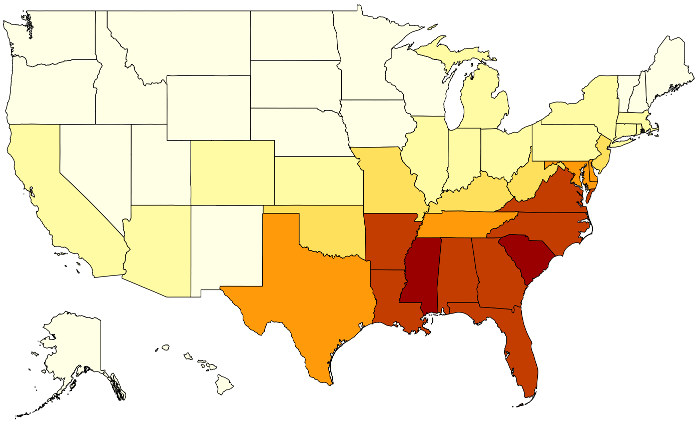
Figure D.1: Historical Black shares



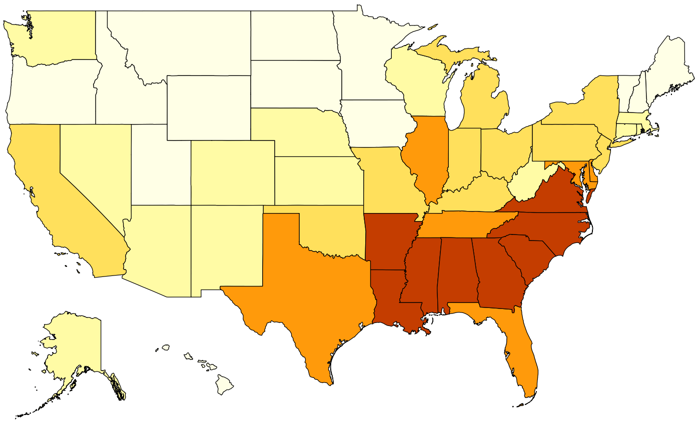
(a) 1860



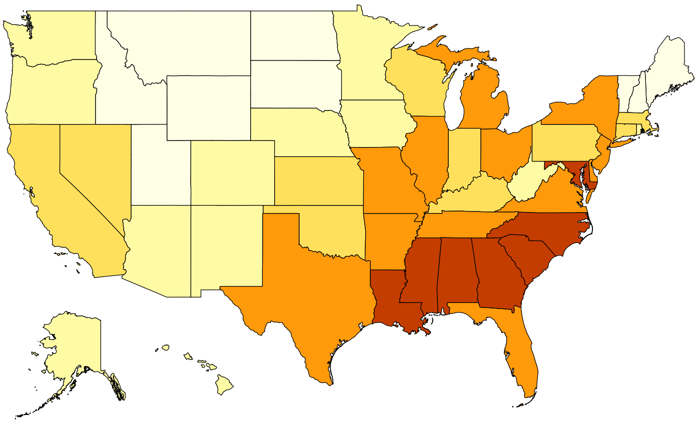
(b) 1890



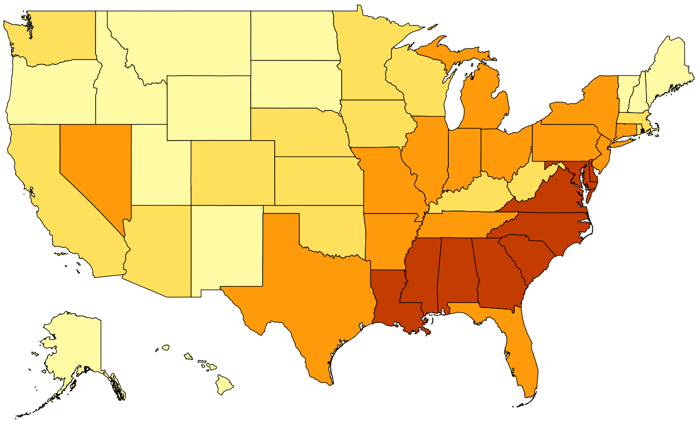
(c) 1930



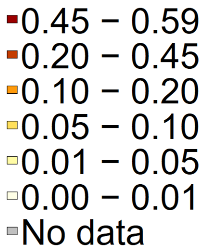
(d) 1960



(e) 1990



(f) 2020

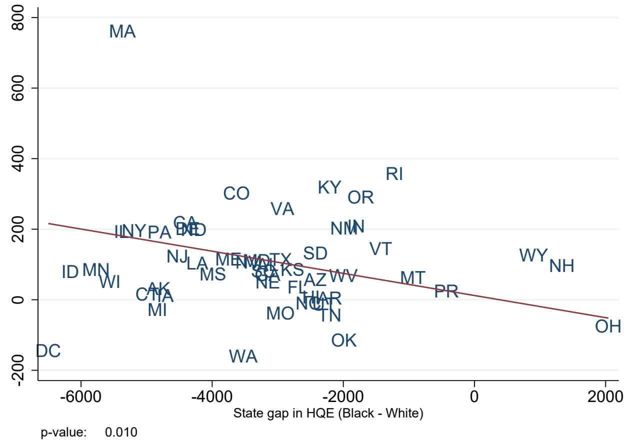


Notes: This figure shows historical Black share the population for all states from 1860 to 2020. The source data is Census Bureau estimates (Gibson and Jung, 2002).

Figure D.2: Correlation between state premium on work history characteristics and racial gaps in work history characteristics

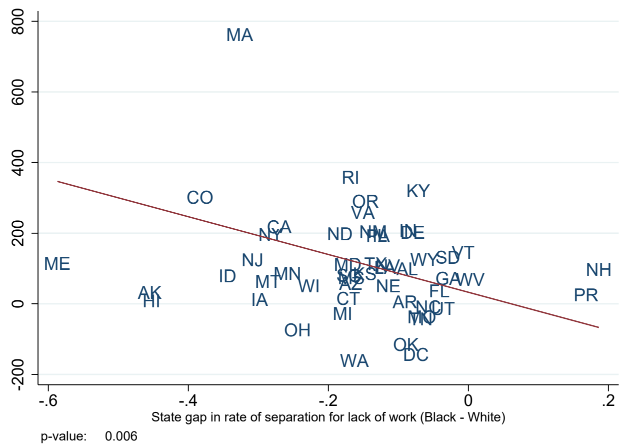
(A) State premium on work history &
State racial gap in Index for work history

(B) State premium on work history &
State racial gap in highest quarter earnings



(C) State premium on work history &
State racial gap in base period earnings

(D) State premium on work history &
State racial gap in rate of separation for lack of work



Note: In all panels, we present in the y-axis an Index of the overall state premium on work history. It corresponds the average premium on their Weekly Benefit Amount that all U.S. claimants would receive, if the rules of state k were implemented in all the U.S.: $\hat{\alpha}_{1,k} \cdot \overline{X}$ (notations explained in Section 3.1). Each panel presents a specific measure of the gap in work history characteristics in the x-axis: an Index of all work history in Panel (A), highest quarter earnings in Panel (B), base period earnings in Panel (C), and the rate of separation for lack of work (D). The Index of all work history corresponds to the Weekly Benefit Amount that a claimant i with these specific work history characteristics should receive given the average UI rules across states: $\hat{\overline{\alpha}}_1 \cdot X_i$. We present the regression line and the corresponding p-value, obtained when each state is weighted by its number of claimants.

Table D.2: Robustness checks: Black-white gaps in monetary determinations—Estimates obtained with various measures of claimants' work history variables

	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	-73.654***	-0.033***	-73.654***	-0.033***	-73.654***	-0.033***
	(1.533)	(0.000)	(1.533)	(0.000)	(1.533)	(0.000)
(i) Explained by State Rule differences	-14.627***	-0.019***	-14.237***	-0.021***	-13.605***	-0.019***
	(0.409)	(0.002)	(1.431)	(0.002)	(1.924)	(0.004)
(ii) Explained by Work History differences	-57.526***	-0.011***	-62.081***	-0.017***	-60.600***	-0.014***
	(0.014)	(0.002)	(0.301)	(0.003)	(0.329)	(0.002)
(iii) Unexplained	-1.501	-0.003	2.664***	0.005***	0.551	0.001
	(1.138)	(0.004)	(0.403)	(0.000)	(0.720)	(0.003)
White mean	307.058	0.408	307.058	0.408	307.058	0.408
Gap relative to White mean (in %)	-24.0	-8.0	-24.0	-8.0	-24.0	-8.0
(i) relative to White mean (in %)	-4.8	-4.6	-4.6	-5.1	-4.4	-4.8
(ii) relative to White mean (in %)	-18.7	-2.7	-20.2	-4.2	-19.7	-3.5
(iii) relative to White mean (in %)	-0.5	-0.7	0.9	1.2	0.2	0.3
Nb of observations	81,393	81,393	81,393	81,393	81,393	81,393

Notes: In this Table, we present the same estimates as in the first two columns of Table 4, except that we use proxies 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.2. In columns (5) and (6), we present for comparison the results obtained when using the actual monetary work history variables instead of proxies (the estimates are hence the same as those presented in the first two columns of Table 4).

Table D.3: Robustness checks: Black-white gaps in UI—Estimates obtained when including non UI-relevant demographic characteristics in the set of work history variables

	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
	(3.029)	(0.004)	(0.006)	(3.839)	(0.005)
(i) Explained by State Rule differences	-32.969***	-0.034***	-0.077***	-13.119***	-0.014***
	(4.197)	(0.007)	(0.011)	(1.480)	(0.002)
(ii) Explained by Individual characteristics differences	-64.618***	-0.036***	-0.089***	-52.581***	0.021***
	(3.353)	(0.005)	(0.008)	(3.260)	(0.004)
(iii) Unexplained	5.277	0.006	0.023**	-0.654	-0.003
	(4.197)	(0.008)	(0.012)	(1.682)	(0.003)
White mean	274.690	0.356	0.755	363.662	0.472
Gap relative to White mean (in %)	-33.6	-18.3	-18.8	-18.2	0.6
(i) relative to White mean (in %)	-12.0	-9.7	-10.2	-3.6	-3.0
(ii) relative to White mean (in %)	-23.5	-10.2	-11.7	-14.5	4.3
(iii) relative to White mean (in %)	1.9	1.5	3.1	-0.2	-0.7
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 D.4: Robustness checks: Black-white gaps in UI generosity overall—Estimates of UI rule parameters obtained when allowing rules to change within state over time

	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
	(3.393)	(0.004)	(0.007)	(3.698)	(0.005)
(i) Explained by State Rule differences	-22.609***	-0.030***	-0.045***	-12.619***	-0.014***
	(3.291)	(0.005)	(0.009)	(1.870)	(0.003)
(ii) Explained by Work History differences	-64.675***	-0.028***	-0.087***	-52.179***	0.021***
	(1.990)	(0.003)	(0.005)	(3.135)	(0.004)
(iii) Unexplained	-5.027	-0.007	-0.010	-1.556	-0.004
	(3.760)	(0.006)	(0.010)	(2.084)	(0.004)
White mean	274.690	0.356	0.755	363.662	0.472
Gap relative to White mean (in %)	-33.6	-18.3	-18.8	-18.2	0.6
(i) relative to White mean (in %)	-8.2	-8.5	-6.0	-3.5	-2.9
(ii) relative to White mean (in %)	-23.5	-7.8	-11.5	-14.3	4.4
(iii) relative to White mean (in %)	-1.8	-2.0	-1.4	-0.4	-0.8
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 that the state rule parameters are allowed to vary over time (the α parameters in model(1)). We split the time window into three periods (before 2008, 2008-2013, after 2013), and estimate a specific set of UI-rule parameters for each (156) state$\times$periods.

Table D.5: Robustness check: Black-white gaps in UI generosity overall—Estimates of UI rule parameters obtained 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	-92.310***	-0.065***	-0.142***	-66.354***	0.003
	(3.150)	(0.004)	(0.006)	(3.314)	(0.005)
(i) Explained by State Rule differences	-42.290***	-0.045***	-0.064***	-14.573***	-0.016***
	(4.107)	(0.007)	(0.005)	(1.369)	(0.002)
(ii) Explained by Work History differences	-56.734***	-0.020***	-0.083***	-53.720***	0.017***
	(1.790)	(0.004)	(0.004)	(2.970)	(0.004)
(iii) Unexplained	6.714*	0.000	0.005	1.939*	0.002
	(3.872)	(0.007)	(0.007)	(1.171)	(0.002)
White mean	274.690	0.356	0.755	363.662	0.472
Gap relative to White mean (in %)	-33.6	-18.3	-18.8	-18.2	0.6
(i) relative to White mean (in %)	-15.4	-12.7	-8.5	-4.0	-3.4
(ii) relative to White mean (in %)	-20.7	-5.7	-11.0	-14.8	3.6
(iii) relative to White mean (in %)	2.4	0.0	0.7	0.5	0.5
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 the state rule parameters are estimated (the α parameters in model(1)) using the random forests algorithm. The state-level hyperparameters were chosen using 150 iterations of a random grid search with 5-fold validation. The standard errors are calculated using a bootstrap with 50 iterations, in each case using the same set of optimal hyperparameters from the initial grid search.

Table D.6: Robustness check: The contribution of Work History differences to the racial gaps, using Kitagawa-Oaxaca-Blinder decomposition

	Overall		Extensive margin	Intensive margin	
	Weekly benefits	Replacement rate	Approved	Weekly benefits if approved	Replacement rate if approved
	(1)	(2)	(3)	(4)	(5)
Differential					
White-Black Gap	-92.310***	-0.065***	-0.142***	-66.354***	0.003
	(7.071)	(0.007)	(0.010)	(7.146)	(0.008)
Decomposition					
Gap explained by Work History	-74.044***	-0.031***	-0.107***	-55.501***	0.019***
	(5.386)	(0.004)	(0.008)	(5.659)	(0.005)
Gap unexplained by Work History	-18.266***	-0.034***	-0.035***	-10.852***	-0.016**
	(4.180)	(0.006)	(0.008)	(3.895)	(0.006)
Nb of observations	168,821	168,821	168,821	20,691	20,691

Notes: This table shows the point estimates of the contribution of Work History variables to the racial gaps in UI outcomes, using a Kitagawa-Oaxaca-Blinder decomposition (obtained following Jann (2008)). We include the same work history variables as in Table 3, but instead of allowing the coefficients associated with work history variables to differ across states, we allow them to differ across race groups. The gap unexplained by Work History hence can both reflect differences in state rules for Black and white claimants, and discrimination based on race. Standard errors clustered at the state level are presented in parentheses.

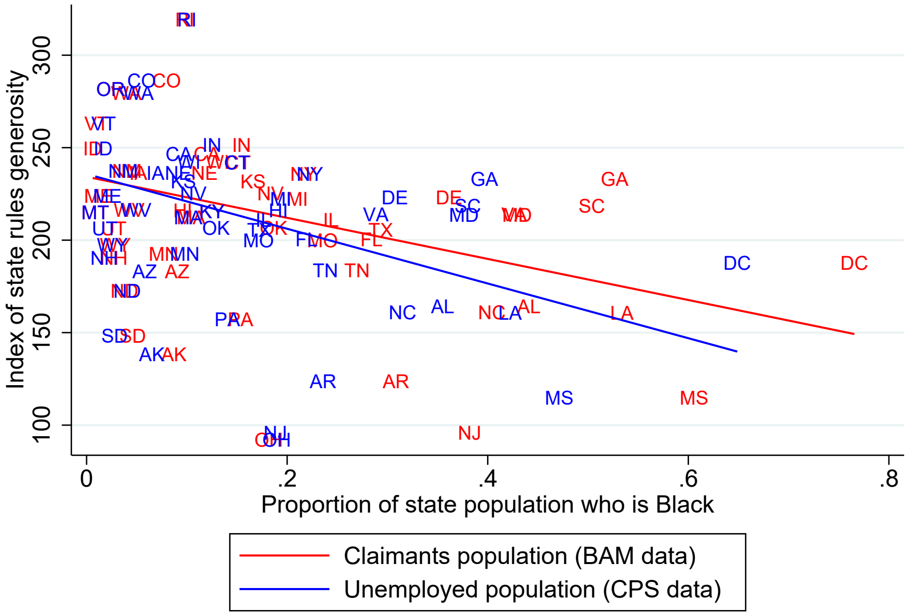
Table D.7: Gaps in UI generosity: Black or Hispanic vs white non-Hispanic

	Overall		Extensive margin	Intensive margin	
	Weekly benefits	Replacement rate	Approved	Weekly benefits if approved	Replacement rate if approved
	(1)	(2)	(3)	(4)	(5)
Black or Hisp vs White non-Hisp Gap	-83.906***	-0.039***	-0.112***	-65.188***	0.020***
	(3.076)	(0.004)	(0.006)	(3.668)	(0.004)
(i) Explained by State Rule differences	-26.334***	-0.020***	-0.039***	-9.176***	-0.010***
	(3.430)	(0.005)	(0.009)	(1.261)	(0.002)
(ii) Explained by Work History differences	-59.767***	-0.020***	-0.077***	-54.791***	0.033***
	(3.060)	(0.004)	(0.007)	(3.152)	(0.004)
(iii) Unexplained	2.196	0.001	0.004	-1.221	-0.003
	(2.631)	(0.005)	(0.008)	(1.162)	(0.002)
White non-Hisp mean	283.566	0.356	0.762	372.344	0.467
Gap relative to White non-Hisp mean (in %)	-29.6	-11.0	-14.6	-17.5	4.2
(i) relative to White non-Hisp mean (in %)	-9.3	-5.5	-5.1	-2.5	-2.1
(ii) relative to White non-Hisp mean (in %)	-21.1	-5.6	-10.1	-14.7	7.1
(iii) relative to White non-Hisp mean (in %)	0.8	0.2	0.6	-0.3	-0.7
Nb of observations	178,973	178,973	178,973	21,641	21,641

Notes: This Table presents the results from the decomposition of the gap in UI between Black or Hispanic and white non-Hispanic claimants. The sample is made of Black or Hispanic and white non-Hispanic claimants, instead of Black and white claimants only as in Table 3. The Table follows the same format as Table 3: the first line presents the size of the raw gap and 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 3.1 for details). We present in parentheses bootstrapped standard errors obtained using 1000 iterations. In the bottom part of the Table, we present these gaps in relative terms, i.e. divided by the mean UI outcome for white non-Hispanic claimants.

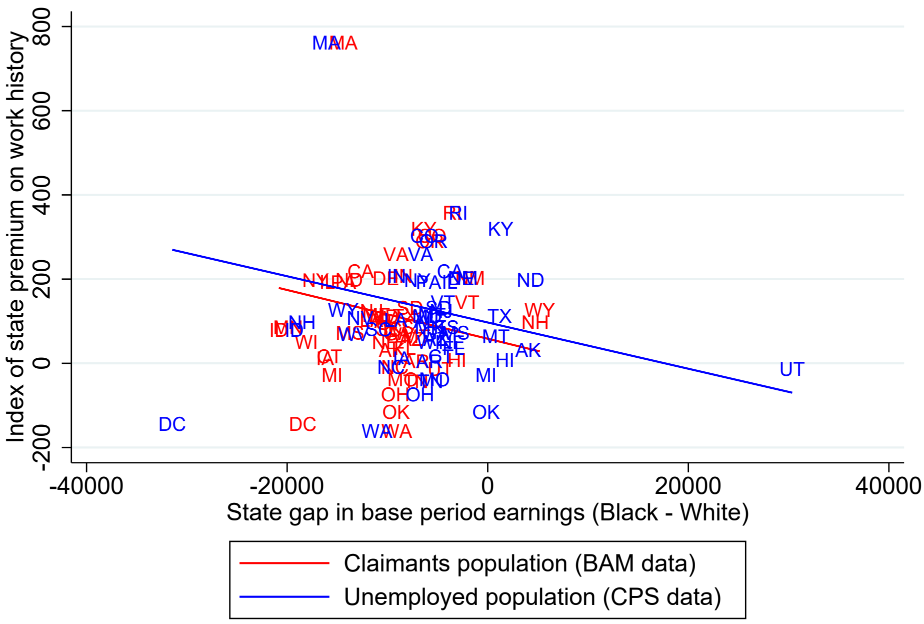
Figure D.3: Characteristics of Black and white workers across states, in the population of claimants and in the population of unemployed

(1) State rules generosity and share of Black individuals, in the population of claimants and in the population of unemployed



p-value of test Claimants=Unemployed: 0.640

(2) State premium on work history and racial gap in prior earnings, in the population of claimants and in the population of unemployed



p-value of test BAM=CPS: 0.971

Notes: In Panel (1), we present the correlation of state generosity in UI rules with the fraction of UI claimants who is Black (in red) and with the fraction of unemployed workers who is Black(in blue). In Panel (2), we present the correlation of state premium on work history with 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.

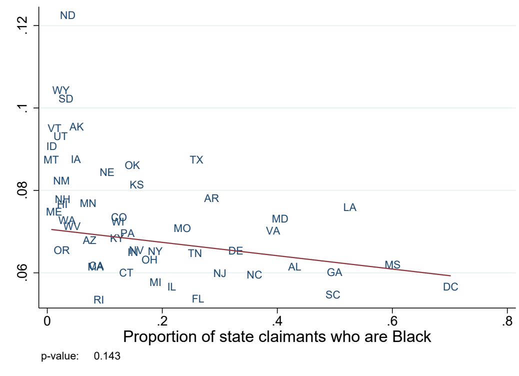
Table D.8: Simulated Black-white gap in UI generosity, for the full population of unemployed workers

	Actual gap among claimants		Simulated gap among unemployed	
	Week benefits (1)	Rep rate (2)	Week benefits (3)	Rep rate (4)
Overall explained Gap	-95.469	-0.066	-80.932	-0.051
(i) Explained by State Rule	-30.724	-0.030	-26.943	-0.026
(ii) Explained by Work History	-64.745	-0.036	-53.988	-0.025
White mean	274.690	0.356	268.797	0.349
Gap/White mean	-34.8	-18.6	-30.1	-14.5
(i)/White mean	-11.2	-8.4	-10.0	-7.3
(ii)/White mean	-23.6	-10.2	-20.1	-7.2

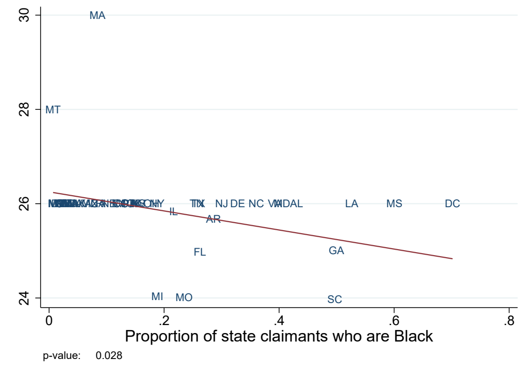
Notes: This table shows the decomposition of the actual and simulated racial gap in UI outcomes in various populations. In col (1) and (2), we consider population of BAM claimants, similar to our main analysis (Table 3). In columns (3) and (4) we consider the population of BAM claimants modified so that, in each state, Black and white claimants have the same population size and the same average base period earnings as Black and white unemployed workers (as measured in the CPS). The decomposition is the same as the one used in our main analysis, but we only present the two explained components (i.e. excluding the unexplained gap).

Figure D.4: Correlation between key labor market statistics and the share of Black claimants

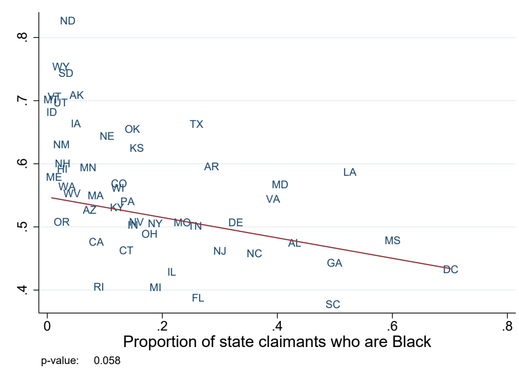
(1) **Weekly transitions from unemployment to employment (i.e. s)**



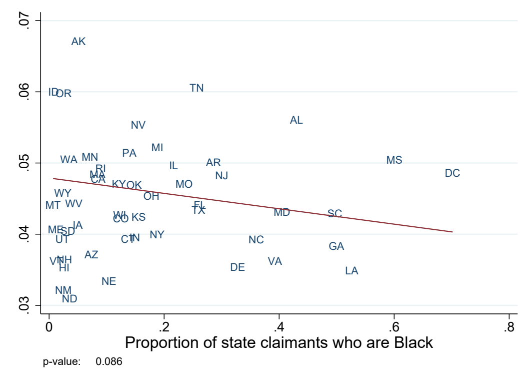
(2) **Maximum benefits duration (i.e. P)**



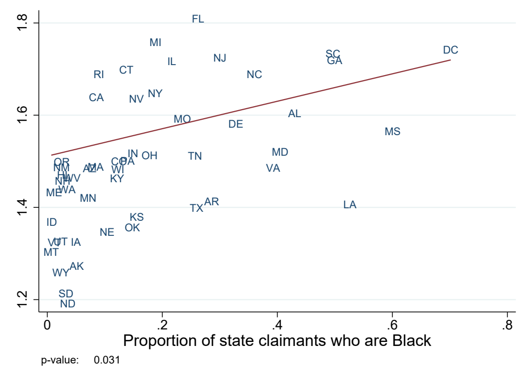
(3) **Ratio $\frac{dB}{db}$ over $\frac{dD}{db}$ (i.e. ξ)**



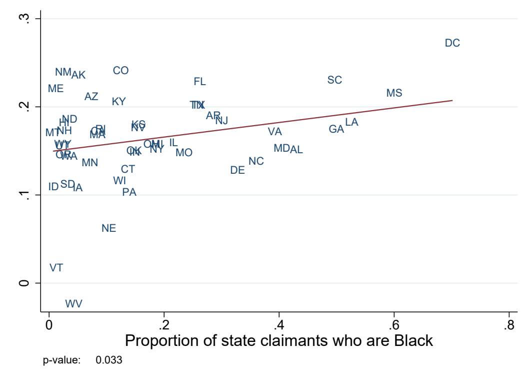
(4) **Ratio of UI tax rate over UI replacement rate (i.e. $\frac{\tau}{b}$)**



(5) **Inverse rate of unemployed duration shorter than P (i.e. $\frac{1}{1-S_p}$)**



(6) **Relative earnings drop with at job loss (i.e. $\frac{c_e - c_{u,t\leq P}}{c_e}$)**



Notes: This Figure shows the correlation across states between the proportion of UI claimants who are Black 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 C.1 (more details are provided in Appendix C). We present the regression line and the corresponding p-value, obtained when each state is weighted by its number of claimants.

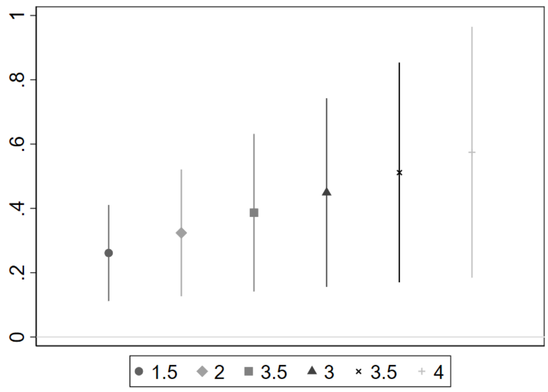
Table D.9: Elasticity of benefits duration and of unemployment duration with respect to benefits amount

	Log(Weeks of paid benefits)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Benefits amount)	0.155***	0.188***		0.113***	0.143***	
	(0.016)	(0.019)		(0.014)	(0.022)	
Log(Benefits amount) × Share of Black		-0.184**			-0.171*	
		(0.089)			(0.091)	
Log(Benefits amount) × Q1			0.166***			0.123***
			(0.019)			(0.025)
Log(Benefits amount) × Q2			0.175***			0.139***
			(0.021)			(0.018)
Log(Benefits amount) × Q3			0.157***			0.102***
			(0.019)			(0.016)
Log(Benefits amount) × Q4			0.098**			0.084**
			(0.045)			(0.036)
BPE x State FE	Yes	Yes	Yes	Yes	Yes	Yes
HQE x State FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual covariates	Yes	Yes	Yes	Yes	Yes	Yes
Elasticity of unemployment duration	0.163			0.119		
Elasticity of unemployment duration in Q1			0.173			0.129
Elasticity of unemployment duration in Q2			0.183			0.145
Elasticity of unemployment duration in Q3			0.164			0.107
Elasticity of unemployment duration in Q4			0.103			0.088
Nb of observations	214,578	214,578	214,578	234,574	234,574	234,574

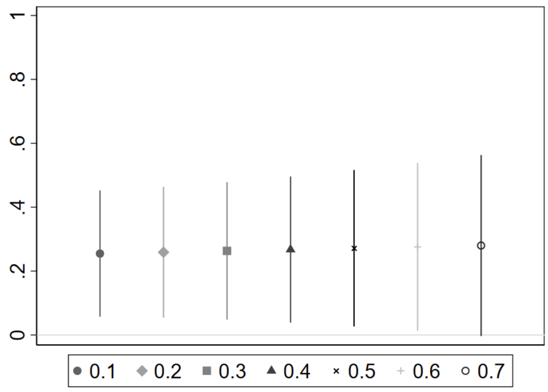
Notes: The Table presents the results from regressions of the logged weeks of paid benefits at the time of an audit on the logged weekly benefits amount, sometimes interacted with the share of Black claimant in the state, or a dummy indicating that the state is in a given quartile of the distribution of the share of Black claimants (e.g., states in Q1 have smallest fraction of Black claimants). Individual covariates include: race, gender, education level, age, citizenship status, reason for separation, number of employers in the base period, recall status, potential benefits duration. We control in various ways for the most important variables for benefits computations, the Base Period Earnings (BPE) and the Highest Quarter Earnings (HQE). The sample includes eligible claimants whose potential benefits duration is at the maximum of their state. In col (1)-(3), we use actual HQE, and further restrict our sample to state×years where we observe this variable; in col (4)-(6), we don't do additional sample restrictions, and use a proxy for HQE (see Section 2.4). For identification, we use that benefits are a non-linear function of BPE and HQE in each state. Robust SE clustered at the state level are reported in parentheses. The coefficients associated with the logged replacement rate give the elasticity of *benefit duration at the time of audits* w.r.t replacement rate. In the bottom part of the Table, we re-scale them to obtain estimates for the elasticity of *unemployment duration* (see Appendix C.3).

Figure D.5: Correlation between the marginal welfare effect of a UI increase and the share of Black claimants, for alternative calibrations

(1) Risk aversion coefficient

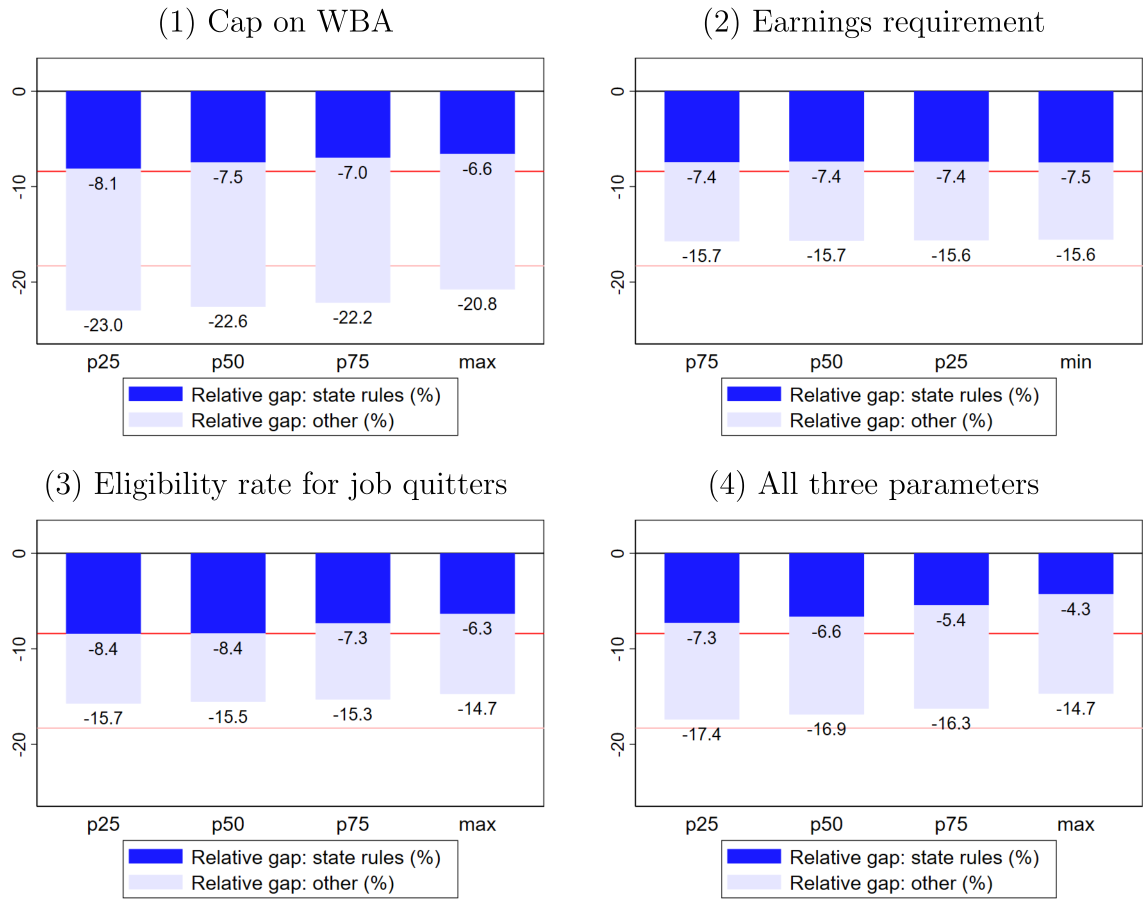


(2) Elasticity of unemployment duration wrt UI benefits



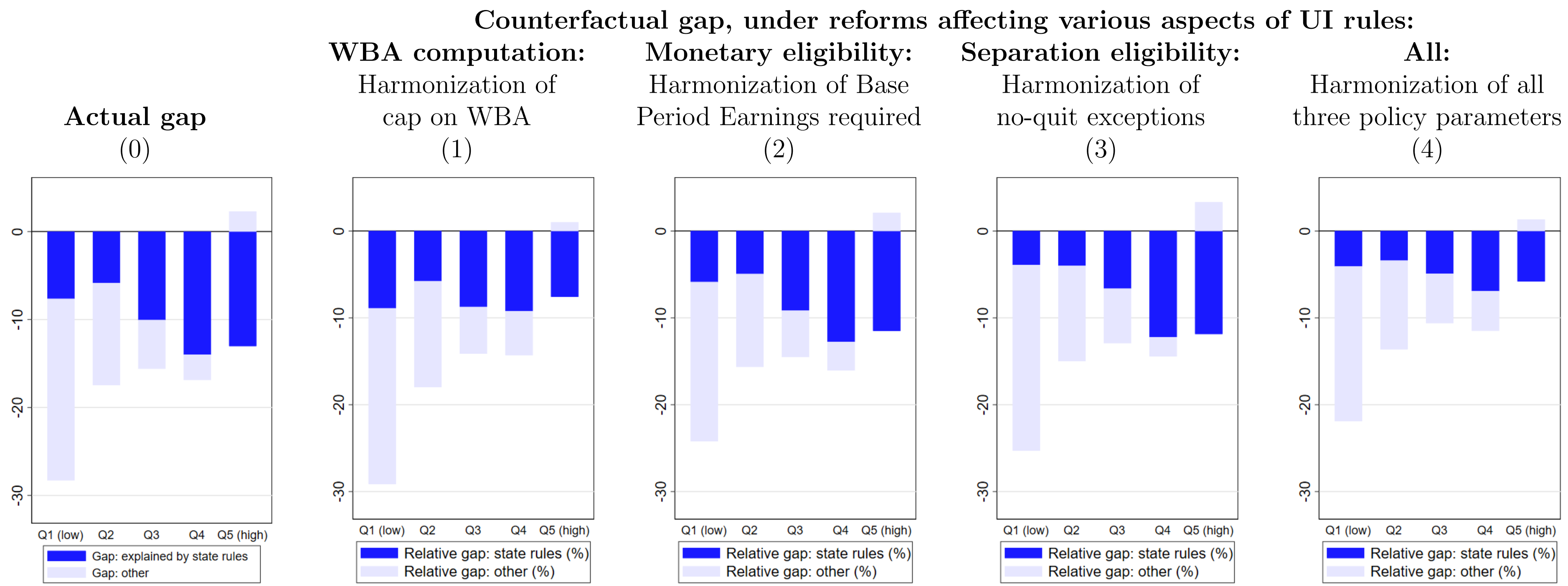
Notes: These Figures present the marginal welfare effect of a UI, using the same calibration as that presented in Table C.1, except for the values of the risk aversion coefficient in Panel (1), and of the elasticity of unemployment duration with respect to benefits in Panel (2).

Figure D.6: Policy simulation



Notes: We present the racial gap under various hypothetical policy reforms: if we harmonize the cap on WBA (in (1)), the minimum BPE required for eligibility (in (2)), and the rate of eligibility for job quitters (in (3)), and all of the three (in (4)). We successively 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 each simulated reform, the horizontal bar represents the gap in replacement rate relative the mean replacement rate of white claimants (%), and the part in dark blue represents the gap explained by state rule differences relative the mean replacement rate of white claimants (%). The red horizontal lines denote the actual relative gaps in replacement rate: the 18.3% overall gap and the 8.4% gap explained by state rule differences (see Table 3).

Figure D.7: Heterogeneity in the actual and simulated racial gaps, across prior wage quintile

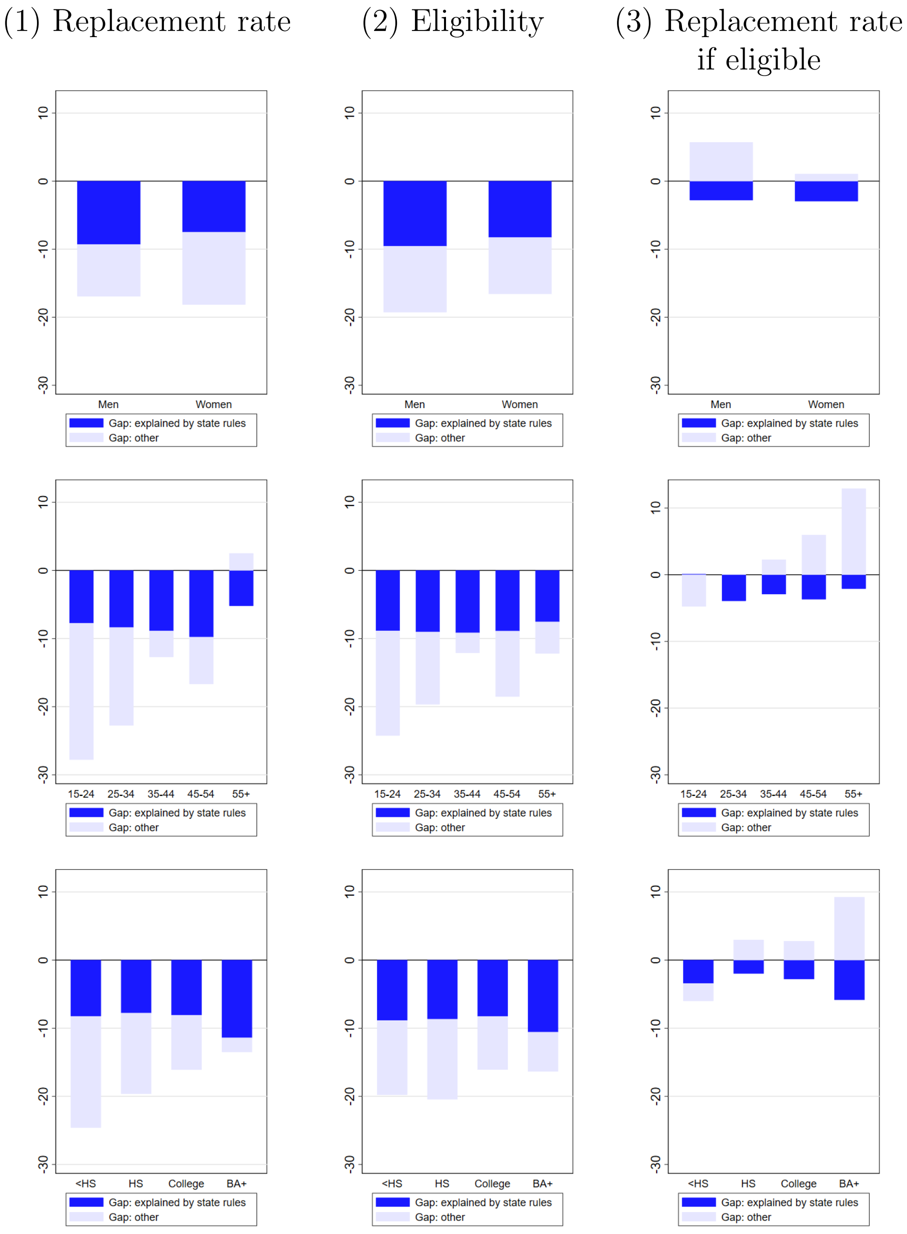


Note: We present the gap in replacement rate obtained if we harmonized each of the four policy parameters considered (set to the maximum generosity level). The y-axes always represent the magnitude of the relative gaps in %. We show separately the gaps for claimants in various quintiles of the distribution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

Figure D.8: Gaps in replacement rate, between various demographic 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 replacement rate in relative terms (%). The full bar represents the total gap, and the bar in dark blue represents the gap explained by state rule differences.

Figure D.9: 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 gives the magnitude of the relative gaps in %. We show separately the gaps for men and women, for claimants in different age groups, with different education levels (less than high school degree, high school degree, attended college, bachelor degree or above).

Table D.10: Mistakes in the assessment of work history variables

	Mistakes in monetary work history variables:								
	Any mistake			Positive mistake			Negative mistake		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	0.976	1.003	1.003	1.144	1.192	1.135	0.940	0.972	0.981
	(0.086)	(0.090)	(0.089)	(0.269)	(0.296)	(0.269)	(0.077)	(0.079)	(0.082)
White Mean	0.038	0.038	0.038	0.008	0.008	0.008	0.029	0.029	0.029
StateXYear FE	×	×	×	×	×	×	×	×	×
Original UI determination		×	×		×	×		×	×
Demographic characteristics			×			×			×
N	168,821	168,821	168,821	168,821	168,821	168,821	168,821	168,821	168,821
	Mistakes in separation work history variables:								
	Any mistake			Positive mistake			Negative mistake		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	1.763***	1.843***	1.697**	1.701**	2.134***	2.058**	2.169*	3.564	4.135
	(0.340)	(0.436)	(0.436)	(0.359)	(0.582)	(0.647)	(0.899)	(2.853)	(3.592)
White Mean	0.006	0.006	0.006	0.006	0.006	0.006	0.001	0.001	0.001
StateXYear FE	×	×	×	×	×	×	×	×	×
Original UI determination		×	×		×	×		×	×
Demographic characteristics			×			×			×
N	168,821	168,821	168,821	168,821	168,821	168,821	168,821	168,821	168,821

Notes: This table presents estimates from the Poisson regression of dummies indicating that mistakes were detected during BAM audits, on claimants' self-reported race. We report the exponentiated coefficients (incidence-rate ratios). We focus on mistakes concerning the measurement of base period earnings in the upper Table, and in the measurement of the reason for separation in the lower Table. When the original determinations were excessively favorable (resp. unfavorable) to claimants, the mistakes are considered positive (resp. negative). We control for the original determinations, and additionally include state×year fixed effects and demographic variables in some specifications (gender, age, education). We report robust standard errors clustered at the state×year level.