NBER WORKING PAPER SERIES

RACIAL INEQUALITY IN THE U.S. UNEMPLOYMENT INSURANCE SYSTEM

Daphné Skandalis
Ioana Marinescu
Maxim N. Massenkoff

Working Paper 30252
http://www.nber.org/papers/w30252

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2022, Revised October 2022

We thank for their help with accessing and understanding various datasets and/or for their feedback Antoine Bertheau, Ellora Derenoncourt, Steven Durlauf, Eliza Forsythe, Nicole Fortin, Alix Gould-Werth, Peter Ganong, Nikolaj Harmon, Patrick Kline, Per Krusell, Camille Landais, Thomas le Barbanchon, Pauline Leung, Bruce Meyer, Robert Moffitt, Andreas Mueller, Suresh Naidu, Arash Nekoei, Matthew Notowidigdo, Laura Pilossoph, Tobias Renkin, Evan Rose, Luke Shaefer, Benjamin Shoefer, Jakob Søgaard, Georges Skandalis, Shu Lin Wee, Stephen Woodbury, the participants of the CREST-IZA workshop, the European Labor Symposium for Early Career Economists, the Seminars of IFS STICERD, SOFI, IIES, Cornell, Bank of Canada, University of British Columbia, Boston College, Harris School of Public Policy, the University of Munich, the Zurich-Lausanne Workshop on “Job Search and the Labor Market”, the Berkeley-Princeton Workshop on “Racial and Ethnic Disparities in the Economy”, the NBER Summer Institute, CEPR-Bank of Italy Workshop: Labour market policies and institutions. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Racial Inequality in the U.S. Unemployment Insurance System
Daphné Skandalis, Ioana Marinescu, and Maxim N. Massenkoff
NBER Working Paper No. 30252
July 2022, Revised October 2022
JEL No. J65,J7

ABSTRACT

The U.S. unemployment insurance (UI) system operates as a federal-state partnership, where states have considerable autonomy to decide on specific rules. This has allowed for systematically stricter UI rules in states with a larger Black population. In this paper, we study how these differences in state rules create racial inequality in unemployment insurance, using administrative data from random audits on UI claims in all states. We first document a large gap in the UI that Black and White unemployed workers receive after filing a new claim. Compared to White claimants, Black claimants receive an 18:3% lower replacement rate (i.e., benefits relative to prior wage, including zero benefits for denied claimants). We then decompose this gap. In principle, the replacement rate of each claimant mechanically depends on the rules in her state and on her work history (e.g., the earnings before job loss and the reason for separation from prior employer). Since we observe claimants' UI-relevant work history and state, we are in a unique position to identify the role of each factor. After accounting for Black-White differences in work history, we find that differences in rules across states create an 8:4% Black-White gap in replacement rate (i.e., close to half of the overall gap). Using a standard welfare calculation, we finally show that states with the largest Black population would gain the most from having more generous UI rules. Altogether, our results highlight that disparate UI state rules create racial inequality without maximizing overall welfare.

Daphné Skandalis
University of Copenhagen
Øster Farimagsgade 5
1353 Copenhagen
Denmark
dskandalis@gmail.com

Ioana Marinescu
University of Pennsylvania
School of Social Policy & Practice
3701 Locust Walk
Philadelphia PA, 19104-6214 and
IZA
ioma@upenn.edu

Maxim N. Massenkoff
Graduate School of Defense Management
Naval Postgraduate School
Monterey, CA 93943
maxim.massenkoff@nps.edu

1 Introduction

In the U.S., there are large and persistent racial income disparities. While social insurance and income-based redistribution programs could help alleviate these disparities, Black people facing economic difficulties often have less access to these programs.[1] In particular, Black unemployed workers are less likely than White unemployed workers to benefit from unemployment insurance (UI), the main source of income during unemployment (e.g., Nichols and Simms, 2012; Gould-Werth and Shaefer, 2012). Yet, Black workers stand to gain the most from UI, as they hold little liquid wealth to smooth their consumption (Ganong et al., 2021) and face more difficulties finding new jobs due to racial discrimination in hiring (Kline, Rose, and Walters, 2021). Several factors might create a gap in unemployment insurance between Black and White claimants. First, factors outside of the UI system might play a role: Black claimants may have a less favorable work history at the time when they lose their job (e.g., lower earnings in the preceding quarters, or voluntary separation from the last employer), which would undermine their eligibility for UI. Second, the design of the decentralized UI system might also contribute to the gap: because UI rules are systematically less generous in states with a larger Black population (Figure 1), Black claimants may receive lower unemployment insurance, even when they have the same work history as White claimants. Besides, Black workers might also experience discrimination in the treatment of their UI claim.

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

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

received by eligible claimants (i.e. the intensive margin), and the gap in the eligibility rate (i.e. the extensive margin).

We start by presenting new descriptive statistics about unemployment insurance in the U.S. We document that states with a larger Black population have systematically stricter rules for all aspects of unemployment insurance: the eligibility requirements are tougher, there is a lower cap on the weekly benefits eligible claimants can receive, etc. We then describe the claiming process: strikingly, we show that as many as 28% of new claimants are found ineligible. The replacement rate (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 that of White claimants. The rest of the paper explores where this racial gap in claimants' replacement rate is coming from.

In principle, the replacement rate of claimants mechanically depends on the rules in their state and on their work history. We decompose the gap in the replacement rate that Black and White claimants receive into three factors: differences in individual work history, differences in the rules prevailing where the claimant lives, and residual differences. We can credibly isolate the contribution of each factor since we observe virtually all variables used to determine claimants' eligibility and benefit amounts, according to UI rules: earnings during the base period, earnings during the highest quarter, number of weeks worked during the base period, the reason for separation. For a small number of claimants, some of these variables are missing. We proxy these variables, using predictions based on claimants' other characteristics, such as age, gender, race, prior occupation, prior industry and prior wage, and show in robustness checks that our results are not sensitive to the use of proxies. We use a Oaxaca-Blinder style decomposition of the Black-White gap: we first estimate the state rule parameters by regressing UI outcomes on work history variables state by state in the sample of White claimants only, and we then use these estimated parameters to compute each component of the racial gap.

Why do Black UI claimants receive an 18.3% lower replacement rate than White claimants? We find that racial differences in work history cause a 10.2% gap, accounting for a little over half of the difference. Though the gap explained by work history differences is large, it is striking that a large part of the racial gap in UI is *not* explained by differences in work history. Where is it coming from? Our decomposition shows that differences in state-specific rules cause Black claimants to have an 8.4% lower replacement rate than White claimants. This finding highlights that institutions play a key role in generating racial inequality: the design of the decentralized UI system directly generates new gaps in income between Black and White claimants, even when they have the same work history. Finally, we find no residual racial gap once we account for state rules and work history differences. The absence of a residual gap suggests that there is no discrimination against Black claimants in the implementation of the UI rules.

We then analyze separately the gap in eligibility (extensive margin) and in the replacement rate of eligible claimants (intensive margin). Black claimants are 18.8% less likely to be eligible. A 9% gap in eligibility is due to state-specific rules, while the rest of the gap is explained by work history, again with no unexplained component. When eligible, Black claimants have the same replacement rate as White claimants, but this masks differences of treatment across states. The UI system is progressive for eligible claimants: eligible claimants with higher prior earnings receive a lower replacement rate due to a cap on the Weekly Benefit Amount. Since eligible Black claimants tend to have lower earnings, they would receive a higher replacement rate if UI rules were the same in all states. In fact, differences in state rules generate a 3% Black-White gap in replacement rate among eligible claimants, which turns out to fully offset the boost in UI that Black claimants obtain from the progressivity of the UI system. Overall, this analysis shows that differences in state rules generate racial inequality in both the extensive and the intensive margin of UI.

Additionally, we show that our finding of an 8.4% racial gap among claimants caused by state rule differences generalizes to the *full population of unemployed workers*. To do that, we compare the population of newly unemployed workers in the Current Population Survey (CPS) and the population of claimants in our BAM study sample. We find that the two populations are similar in the dimensions that matter for the racial gap caused by state rule differences, in particular in the over-representation of Black people in states with stringent UI rules. We then directly calculate the magnitude of the racial gap explained state rule differences in the population of unemployed workers, that is implied by their characteristics in the CPS. We modify the sample of BAM claimants by rescaling the average base period earnings and the population size in each state and each race group, to match their levels among CPS unemployed workers. We predict the replacement rates in this simulated sample, using the estimated state-specific UI rule parameters from our main analysis. We find that state rule differences would cause a racial gap in UI in the full population of unemployed that is similar to the one we estimated in the population of claimants. Overall, our analysis hence indicates that unemployed workers don't select into claiming UI in a way that amplifies the role of state rule differences.

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

Finally, we expand the discussion on the role of state rule differences in racial inequality in UI, with three additional analyses. First, we offer a brief policy discussion, simulating the effect of various reforms aimed at reducing the racial inequality caused by differences in rules across states. We find that relaxing unemployment insurance eligibility requirements in the strictest states is a promising option if one wants to both reduce racial inequality in the UI system and increase the generosity of the UI system for low-earnings workers. Second, we analyze gaps in UI for claimants who differ in dimensions other than race. We show that, although we observe raw gaps for claimants from different genders, age groups or education levels, state rule differences do not play a substantial role. The role of state rule differences hence appears specific to the racial gap. Third, we examine another potential source of racial inequality in the UI system: the way work history variables are measured could be racially biased—even if there is no bias in the way claimants are treated conditional on their measured work history. We analyze the mistakes in the assessment of work history variables that were detected during the BAM audits. We find no evidence of anti-Black racial bias in the assessment of work history variables.

Our findings contribute to the vast literature on racial inequality in economic outcomes. We are in the unique position to highlight the role of *institutions*: in most cases, it is difficult to disentangle institutional factors from individuals' discriminating behavior. In the setting of unemployment insurance, institutional rules determine benefit calculation based on work history, which we can precisely measure. This allows us to show that the design of the UI institution generates unequal insurance coverage for claimants of different races but with the same work history—without involving any discriminatory behavior by individuals. Historically, the economic literature might have underappreciated the role of institutions due to its focus on intentional discrimination by individuals (Small and Pager, 2020; Bohren, Hull, and Imas, 2022). We are contributing to a recent strand of empirical studies highlighting how the design of rules and institutions creates racial inequality.[2] In particular, Derenoncourt and Montialoux (2021) show that occupational exclusions from the federal minimum wage instated in 1938 largely contributed to the racial wage disparities in the following decades. While it is beyond the scope of our paper to analyze why states exhibit these specific differences in generosity in the UI system, we note that our results are consistent with the idea that racial diversity tends to prevent the enactment of generous social policies (Alesina, Glaeser, and Sacerdote, 2001).[3]

Second, our paper contributes to the analyses of unemployment insurance recipiency. A large literature has investigated why UI recipiency is low in many countries (Blank and Card (1991), Anderson and Meyer (1997), Shaefer (2010),Fontaine and Kettemann (2019), Auray, Fuller, and Lkhagvasuren (2019), Blasco and Fontaine (2021), Lachowska, Sorkin, and Woodbury (2021)). Our main contribution is to explain why Black workers receive less UI than White workers in the U.S. The racial gap in UI recipiency had long been observed across survey datasets (e.g., Nichols and Simms (2012), Gould-Werth and Shaefer (2012), Kuka and Stuart (2021)).[4] However, the role of state rule differences has not been precisely quantified. Surveys, like the Survey of Income and Program Participation (SIPP), do not allow to isolate the role of state rule differences, because survey data do not contain information on who claimed UI, nor on the exact work history variables used by the UI administration. We further discuss the datasets on UI used in prior literature in section 3.3.

Third, our paper is related to welfare analyses of unemployment insurance. A rich literature offers a framework to determine which level of UI generosity maximizes welfare, based on various measurable statistics (e.g., Baily (1978a), Chetty (2006),Schmieder and von Watcher (2016)). Using this framework, prior studies have measured how the welfare gains from UI extensions might change over the business cycle (Kroft and Notowidigdo (2016a), Schmieder, von Wachter, and Bender. (2012)). We present the first analysis of differences in the welfare effect of an increase in unemployment benefits across U.S. states.

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

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

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

We show that the marginal welfare effect of additional unemployment benefits increases with the share of Black claimants in the state.

The paper is organized as follows. Section 2 presents the institutional context of unemployment insurance in the U.S. In Section 3, we present the BAM audit data. Section 4 describes our empirical strategy. Section 5 presents new descriptive statistics about UI claims. In section 6, we present our main finding of the racial gap in unemployment insurance explained by state rule differences. The welfare analysis in Section 7 aims to assess whether having stricter rules in states with a larger Black population is optimal. In section 8, we discuss various additional results. Section 9 concludes.

2 Institutional context

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 Since its inception with the Social Security Act of 1935, the U.S. unemployment insurance system has been unique in its level of decentralization, operating as a federal-state partnership (Baicker, Goldin, and Katz, 2007). Within the federal guidelines, state legislatures can determine benefit amounts, duration, and eligibility requirements. In practice, most aspects of UI rules differ widely from state to state.[5] This means that otherwise identical claimants from different states may differ in their eligibility to collect benefits and the level of benefits they are entitled to if eligible. This fact was noticed when unemployment insurance was first established (Reticker, 1942).[6] Historians have also argued that Southern states imposed a decentralized system in 1935 to have the possibility to set a low level of generosity and avoid redistributing income towards their Black residents (Katznelson (2006)). We will document how various aspects of UI rules vary in practice from state to state in Section 5.3.

[5]See https://oui.doleta.gov/unemploy/conformity.aspoverview for more information on the federal guidelines.

[6]Reticker (1942) writes, "So long as State unemployment compensation laws differ in the fractions of wages available as weekly or annual benefits, in minimum and maximum Weekly Benefit Amounts, in methods of rounding, and in uniform and maximum duration, there will be disparity in benefits available under the State laws for claimants with identical wage records" (p 11).

Monetary determinations First, to receive benefits, UI applicants must satisfy "monetary" eligibility criteria, meant to ensure a certain level of labor force attachment. The method to determine monetary eligibility depends on the state. 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.

The Weekly Benefit Amount is a non-linear function of the person's earnings during the base period. Again, 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 can considerably reduce the effective replacement rates, and are also an important source of 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 Claimants must also satisfy non-monetary criteria to become eligible. 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.[7] 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: they systematically ask claimants to fill standardized questionnaires, and collect complementary information through investigative processes when necessary: employer interviews, third-party verification, income verification, etc.

3 Data

3.1 Construction of the study dataset

We collected paid and denied audited claims from the Benefit Accuracy Measurement (BAM) (Woodbury, 2002; Woodbury and Vroman, 2000) for the years 2002-2017. These audit data cover both new claimants (i.e. claimants who are applying to start receiving 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.[8] 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

[7]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`.

[8]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.

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 the denial rate, and compare them to the corresponding statistics available by quarter and state in the DOL table ETA 5159. Our measures and the DOL measures align closely (Figure A.1). We also compare the composition of paid claimants in the BAM sample to that of continuing claimants, available in the Department of Labor's ETA 203 report ("Characteristics of the Insured Unemployed") in Table A.1. Again, the two sources align very closely.

3.2 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.[9] The information on race and ethnicity is collected like in the U.S. Census: claimants have to select one race category (White, Black or African American, Asian, American Indian or Alaska Native, Native Hawaiian or Other Pacific, Islander, Multiple Categories Reported, Race Unknown) and separately report their ethnicity (Hispanic, Not Hispanic, Unknown). In our main analysis, we compare the UI outcomes of claimants who report being Black to those who report being White. In robustness analyses, we compare non-Hispanic Black claimants and Hispanics to non-Hispanic White claimants. 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. 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 the 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 when the claimants who were paid or separation-denied. Second, not

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

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 using 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, in two type of prediction models, and hence construct two types of proxies, specifically designed to address each of the two data limitations ;entioned above. For more details, see Appendix A.2.

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.[10] In our empirical analysis, we implement the decomposition of the racial gap for various UI outcomes: we successively consider UI generosity for eligible and denied claimants together (coding benefits as 0 for those denied), the eligibility status (extensive margin) and weekly benefits for eligible only (intensive margin). We measure UI generosity using both the Weekly Benefit Amount, and the replacement rate: while the Weekly Benefit Amount is the outcome that is directly determined by UI rules, the replacement rate is the more economically relevant outcome, as it measures how much insurance against income loss is provided by the UI system.

3.3 Comparison with other data sources in the literature

We have constructed our dataset from combined audits data to provide rich information on a representative sample of new UI claimants. The data provides a unique opportunity to describe the traits of people who claim UI, and the typical outcomes from UI applications across all U.S. states. While many papers discuss claiming behavior, data on UI claimants are scarce. Three other types of data sources have been used in the literature to learn about UI claimants, and each presents important limitations. First, the CPS Non-Filer

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

supplements were specifically designed to document UI claiming behavior among workers who are unemployed or marginally attached to the labor force (see e.g., Gould-Werth and Shaefer (2012)). But these surveys have been infrequent and their sample size is small. Moreover, they only collect imprecise information on the work history variables relevant for UI determinations.

Second, administrative UI claims state records matched with wage records contain rich information on work history variables and UI outcomes for all claimants in the state (Lachowska, Sorkin, and Woodbury, 2021). Unfortunately these data are collected at the state level, and have never been consolidated for all of the U.S. to our knowledge. Additionally, these records do not contain demographic information such as race for all claimants.

Third, several papers have indirectly backed out information on UI claimants from information on UI recipients, as data on UI recipients have been relatively less scarce. In particular, the Survey of Income and Program Participation (SIPP), and more recently tax data (Larrimore, Mortenson, and Splinter, 2022), have been used to study UI receipt. Analyzing UI receipt among "likely eligible" unemployed workers is one technique for inferring claiming behavior (Blank and Card (1991), Anderson and Meyer (1997), Kuka and Stuart (2021)). It is however very sensitive to the definition of "likely eligible" unemployed workers. To determine which workers are "likely eligible", one needs to reconstruct the work history variables used by the UI administration, which can lead to important measurement error (Anderson and Meyer, 1997).

4 Empirical strategy

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

4.1 Decomposition of the racial gap in UI

The determinants of UI 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.

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:

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

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.

4.2 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:

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

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 3.2 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. For the analysis of the gap among all claimants, we use the first set of proxies. For the analysis of the gap among eligible claimants, we use the actual Base Period Earnings variable and the second set of proxies for the other monetary variables.

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.[11] Then, we analyze racial differences in monetary eligibility (extensive margin) and in UI generosity that monetary eligible claimants might receive if they also satisfy non-monetary eligibility criteria (intensive margin). For this analysis, we restrict our sample to the 90% of observations in the state-months that use the standard set of variables to determine monetary eligibility. In these states, we observe all the relevant work history variables and do not need to use any proxies (Base Period Earnings, Highest Quarter Earnings, Ratio of Highest Quarter Earnings over Base Period Earnings).[12]

Identification assumption As highlighted by Fortin, Lemieux, and Firpo (2011), while decomposition analyses are often treated as pure accounting exercises, correctly attributing to various factors their contribution to population gaps relies on identifying assumptions similar to those from the treatment effects literature. Our estimates identify the contribution of claimants' work history differences, and state rule differences to the racial gaps, if 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 address these concerns, 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 6.3.

5 Descriptive statistics

5.1 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

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

[12] 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.

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 are paid UI and those who are unemployed for any duration. Although the CPS unemployed population represents a very useful benchmark for the BAM claimants population, one must be cautious when comparing different data sources. In particular, we note that 6% of claimants in BAM declare their race is unknown while this is virtually never the case in the CPS, which suggests some classification differences.[13] Therefore, we interpret differences in the racial composition of claimants and unemployed as only suggestive. We discuss further the suggestive evidence on racial differences in UI claiming rates and receipt rates that can be obtained by taking the ratio of the count of claimants over the count of unemployed in Appendix A.3.

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, indicating above average rejection rates for Black claimants (column (2)). We note that the proportion of Black individuals is larger among all unemployed workers than among new unemployed (col (3) and (5)), which reflects the fact that Black workers stay unemployed much longer. We see that UI claimants include 17% of Hispanics, and that they have a higher rejection rate than the other ethnic groups. 58% of UI claimants are men, which is above their proportion in the unemployed population, and men have a lower rejection rate than women. Workers below age 25 appear under-represented in the claimants population and more likely to be rejected. High school graduates are over-represented among claimants (they represent 42% of claimants versus 36% of newly unemployed), while workers with less than a high school diploma, and those with BAs or more are under-represented.

5.2 What is the outcome of claiming?

In Table 2, we show averages of UI outcomes such as the Weekly Benefit Amount and replacement rate, along with the key work history variables used to determine 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

[13] In the CPS, when demographic variables are missing, they are filled using imputation methods exploiting answers in other waves or from other household members. See `https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/imputation-of-unreported-data-items.html`

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. So they tend to receive lower 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.

5.3 UI rules and claimants' characteristics across states

It has been long documented states with a larger Black population systematically have less generous UI rules (Lieberman, 2001b). We provide a first illustration in Figure 1: in the upper map, darker states are those with lower caps on Weekly Benefit Amount (relative to the average wage of claimants in that state). These states hence tend to offer less generous unemployment benefits to their residents. In the bottom map, dark states are those with a larger share of Black claimants. Note that this allocation of the Black population across U.S. states has been very persistent and precedes the introduction of the UI system in 1935 (see Figure D.1). The comparison of these maps indicates that there is a negative spatial correlation between the size of the Black population and UI generosity, as far as the cap on WBA is concerned.

In Figure 2, we provide a precise quantification of the correlation between various measures of UI generosity and the share of Black claimants, weighting states by their number of claimants. First, we summarize all dimensions of UI generosity into one index, by taking the statutory Weekly Benefit Amount that a claimant with average work history characteristics would get, if she lived in the state. Using the notation detailed in Section 4.1, this index for state k can be expressed as: $\hat{\alpha}_{0,k}+\hat{\alpha}_{1,k}\cdot\overline{X}$. Panel (1) shows a clear negative correlation between the share of Black claimants and the index of generosity of state UI rules. The typical Weekly Benefit Amount decreases by $9 for every 10 percentage points increase in the share of Black claimants. Panel (2) shows that the cap on weekly benefits (relative to the mean prior wage of claimants in the state) declines by 2.5 percentage points for each 10 percentage points increase in the share of Black claimants. In Panel (3), we present minimum level of base period earnings required for eligibility (relative to the mean prior wage of claimants in the state): the higher this threshold, the harder it is to be eligible in the state. This ratio increases with the share of Black claimants in the state. In Panel (4), we analyze how frequently states grant eligibility to claimants who quit their prior job. This measure is negatively correlated with the share of Black claimants. Overall, the share of Black claimants is negatively correlated with all the considered dimensions of UI generosity. We provide further statistics on these measures of UI generosity, and on others, in Appendix Table D.1.

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

6 Main results: racial gaps in UI

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

6.1 The overall racial gap in UI

We present our main results in Table 3. Each column corresponds to a UI outcome. The top panel presents the raw Black-White gap in these outcomes, followed by a decomposition into three components: differences in 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. Let's firs 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% less (or \$30.7) 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.

6.2 The racial gap in monetary determinations

After analyzing the determinants of the gap in UI generosity overall, we now focus on monetary determinations. 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 4.2 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), 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 amounts (component (i)) 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).

6.3 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 indeed 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 (Table 4). In our robustness check Table D.2, we focus on the analysis of the outcomes of monetary determinations, and evaluate the sensitivity of our results 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 also not be affected by 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 Oaxaca-Blinder decomposition, where we measure how much of the racial gaps in UI can be explained by work history. The 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 Oaxaca-Blinder decomposition should be similar to the one that we obtain in our main decomposition. The gap unexplained by work history in the 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 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.

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

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

For anyone who claims UI, the process determining UI outcomes based on state, work history, and potentially race, is the same as the one described in model (1). We can hence estimate the components of the racial gap among all newly unemployed workers from some key state-level statistics, just like for claimants. 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. We compare the newly unemployed with the new claimants from our BAM study sample, in the dimensions that matter for the role of state rule differences on the racial gap. In Figure D.3, Panel (1) presents the correlation of state generosity with the fraction of Black claimants (just like in Figure 2), and with the fraction of Black newly unemployed workers. We see that 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 they claim more in those states, but because this is where Black unemployed workers live. Panel (2) presents the correlation of state generosity with the state racial gaps in prior wages among claimants (just like in Figure D.2), and among unemployed workers. Similarly, 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. Overall, newly unemployed workers look similar to claimants in the dimensions that matter for the role of state rule differences on the racial gap.

Figure D.3 hence suggests that the racial gap explained by state rule differences among unemployed workers is similar to the one we estimated among claimants. Next, we directly quantify the size of the racial gap explained by state rule differences among unemployed workers that is implied by these statistics. We simulate the unemployed population: we modify the sample of BAM claimants by 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 gap explained by state rule differences in the two populations is comparable.

7 Welfare analysis

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

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

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

7.2 Calibration

To measure the marginal welfare effect, we assemble from various data sources the statistics related to state-level unemployment, UI benefits and taxes (see Appendix C.2 for more details). We approximate the marginal social value from consumption smoothing using the difference in income between the employed and the UI recipients multiplied by the coefficient of risk aversion (Baily, 1978b; Gruber, 1997; Chetty, 2006; Kroft and Notowidigdo, 2016b; Leung and O'Leary, 2020). We use the standard value 2 for the coefficient of risk aversion in our main calibration, and show that our conclusions remain unchanged for alternative values. We note that using the drop in income associated with unemployment, rather than the drop in consumption might lead us to overestimate the social value. We therefore abstain from interpreting the *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 shocks (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.

Empirical assessments of the welfare effects of UI typically focus on the measure of the elasticity of unemployment duration with respect to UI benefits. While there are many estimates for this elasticity for the U.S., there are no 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), 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, 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 (column (1)). We find that this elasticity significantly *decreases* with the share of Black claimants in the state (columns (2) and (3)). This finding implies that the marginal welfare costs due to behavioral effects are even lower in states with a high share of Black claimants.

7.3 Welfare analysis results

We present the state-level correlation between the share of Black claimants and the marginal social value (consumption smoothing) of a $1 increase in benefits, the marginal behavioral costs, and the marginal overall welfare effects in Figure 3. In Panel (1), we see clearly that the marginal social value increases with the share of Black claimants in the state. This is because the drop in income associated with unemployment is larger in states with a large Black population. Conversely, Panel (2) shows that the marginal cost decreases with the share of Black claimants. This is in part explained by the fact that a larger fraction of workers stay unemployed *after* the maximum benefit duration in states with a higher share of Black claimants. Therefore, even if more generous unemployment insurance tends to lengthen unemployment duration, it has more limited consequences on the duration of *paid* unemployment benefits in states with a higher share of Black claimants. The result presented in Panel (2) is using our conservative assumption that the elasticity of unemployment duration with respect to benefits level is constant across states. Using instead the state-specific estimates obtained in Table D.9 would further accentuate the negative correlation. Finally, Panel (3) shows a positive correlation between the share of Black claimants and the overall marginal effect (i.e. marginal social value minus marginal behavioral cost). Importantly, this does not depend on the relative magnitude of the social value and of the behavioral cost, given that both contribute to increase the marginal welfare effects for states with more Black claimants. Therefore, the positive correlation between the marginal welfare effect of a UI increase and the share of Black claimants is not sensitive to the value of specific parameters. Appendix Figure D.4 confirms that this result holds with alternative parameter values for the elasticity of unemployment duration with respect to benefits, or for risk aversion. Overall, this analysis shows that having less generous unemployment benefits in states with a higher share of Black claimants is not socially optimal. Racial inequality caused by differences in rules across states in the unemployment insurance system cannot be justified as welfare maximizing.

8 Additional results

8.1 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 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.[14]

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

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

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.[15] 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.5.

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.6. First, we see that existing state rule differences cause a large racial gap for claimants in 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).

[15] 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.

8.2 Discussion

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.7, we present graphically the different components of the gaps in Weekly Benefit Amount and in replacement rate between Black and White claimants, between women and men, between claimants below and above 40 years old, and between claimants with more or less than some college education. We present both the overall gap (full bar), and the gap explained by state rule differences (dark blue part of bar). Overall, women, younger and more educated claimants 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.8: Black claimants are similarly disadvantaged across all demographic groups. Overall, these results support our focus on the consequences of the UI system for racial inequality. We note that these results are consistent with the idea that Southern states may have persistently had stricter rules *because of* their large Black population. Future research analyzing to which extend this relation might be causal would be very valuable.

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 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.[16] We successively consider mistakes in the measurement of monetary variables (upper table), and separation variables (lower table). First, we see that mistakes 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,

[16] It should be noted that 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.

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.

9 Conclusion

In this paper, we analyze a novel representative sample of new UI claimants obtained from random audits of UI claims. We first document a raw 18.3% Black-White gap in the replacement rate received by claimants: Black claimants receive a 29% replacement rate vs. 36% for White claimants. Using a 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 gap among all Black and White unemployed workers with the same work history if all unemployed workers were to claim unemployment benefits. We then examine if the differences in rules across states 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. Going towards more harmonized UI rules across states could hence ensure that Black and White claimants with the same work history receive more similar insurance against job loss, and would also increase overall welfare.

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

Most importantly, our paper highlights that the design of the UI rules plays a key role in generating this inequality, rather than discrimination in the implementation of the rules. The UI system is not an isolated case: differences in state-level rules may also generate racial gaps in the receipt of the main welfare cash transfer program for poor families, the Temporary Assistance for Needy Families (Parolin (2021)); differences in the allocation of public spending decided at the city, metropolitan area or county level may generate racial gaps in the quality of public services, like education (Alesina, Baqir, and Easterly (1999)). Beyond local differences, other aspects of the design of ostensibly race-neutral policies can generate large racial disparities that are not justified by the policies' ultimate goals, as demonstrated by Rose (2021) 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.

Bibliography

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

Alesina, Alberto, Reza Baqir, and William Easterly. 1999. “Public Goods and Ethnic Divisions.” *The Quarterly Journal of Economics* 114 (4):1243–1284. URL https://www.jstor.org/stable/2586963. Publisher: Oxford University Press.

Alesina, Alberto, Matteo F. Ferroni, and Stefanie Stantcheva. 2021. “Perceptions of Racial Gaps, their Causes, and Ways to Reduce Them.” Tech. Rep. w29245, National Bureau of Economic Research. URL https://www.nber.org/papers/w29245.

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

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

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

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

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

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

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

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

Blasco, Sylvie and François Fontaine. 2021. "Unemployment Duration and the Take-Up of Unemployment Insurance." URL https://www.ssrn.com/abstract=3767275.

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

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

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

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

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

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

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

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

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

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

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

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

Gilens, Martin. 2000. *Why Americans Hate Welfare: Race, Media, and the Politics of Antipoverty Policy.* Studies in Communication, Media, and Public Opinion. Chicago, IL: University of Chicago Press. URL https://press.uchicago.edu/ucp/books/book/chicago/W/bo3633527.html.

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

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

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

Jann, Ben. 2008. "The Blinder–Oaxaca Decomposition for Linear Regression Models." *The Stata Journal: Promoting communications on statistics and Stata* 8 (4):453–479. URL http://journals.sagepub.com/doi/10.1177/1536867X0800800401.

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

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

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

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

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

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

———. 2021. "Firms and Unemployment Insurance Take-Up." :74.

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

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

Leung, Pauline and Christopher O'Leary. 2020. "Unemployment Insurance and Means-Tested Program Interactions: Evidence from Administrative Data." *American Economic Journal: Economic Policy* 12 (2):159–192. URL `https://www.aeaweb.org/articles?id=10.1257/pol.20170262`.

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

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

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

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

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

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

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

O'Leary, Christopher J. and Stephen A. Wandner. 2020. "An Illustrated Case for Unemployment Insurance Reform." Tech. rep., W.E. Upjohn Institute. URL `http://research.upjohn.org/up_workingpapers/317/`.

Parolin, Zachary. 2021. "Temporary Assistance for Needy Families and the Black–White child poverty gap in the United States." *Socio-Economic Review* 19 (3):1005–1035. URL `https://doi.org/10.1093/ser/mwz025`.

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

Rose, Evan K. 2021. "Who Gets a Second Chance? Effectiveness and Equity in Supervision of Criminal Offenders." *The Quarterly Journal of Economics* 136 (2). URL https://academic.oup.com/qje/article/136/2/1199/6039346?login=true.

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

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

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

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

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

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

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

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

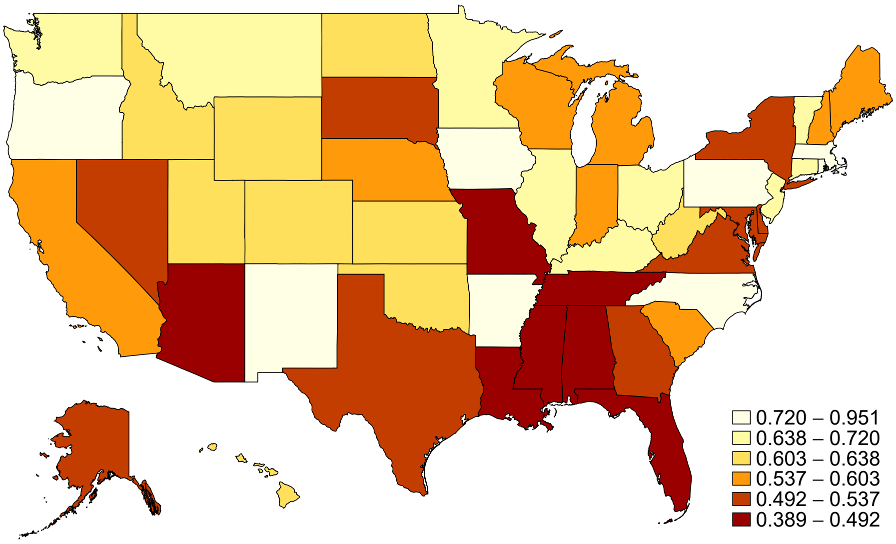
Woodbury, Stephen A. 2002. "Unemployment insurance overpayments and underpayments." .

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

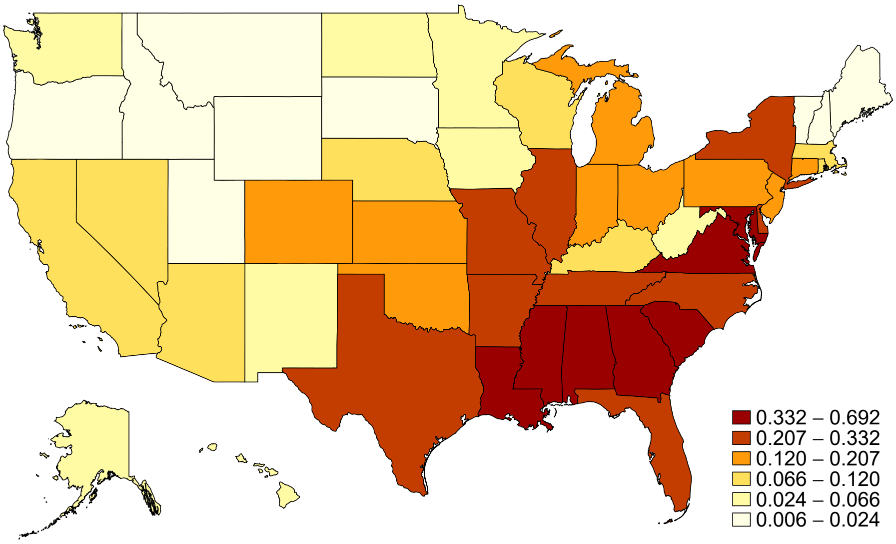
10 Tables and Figures

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

State level of cap on Weekly Benefit Amount, over mean weekly wage

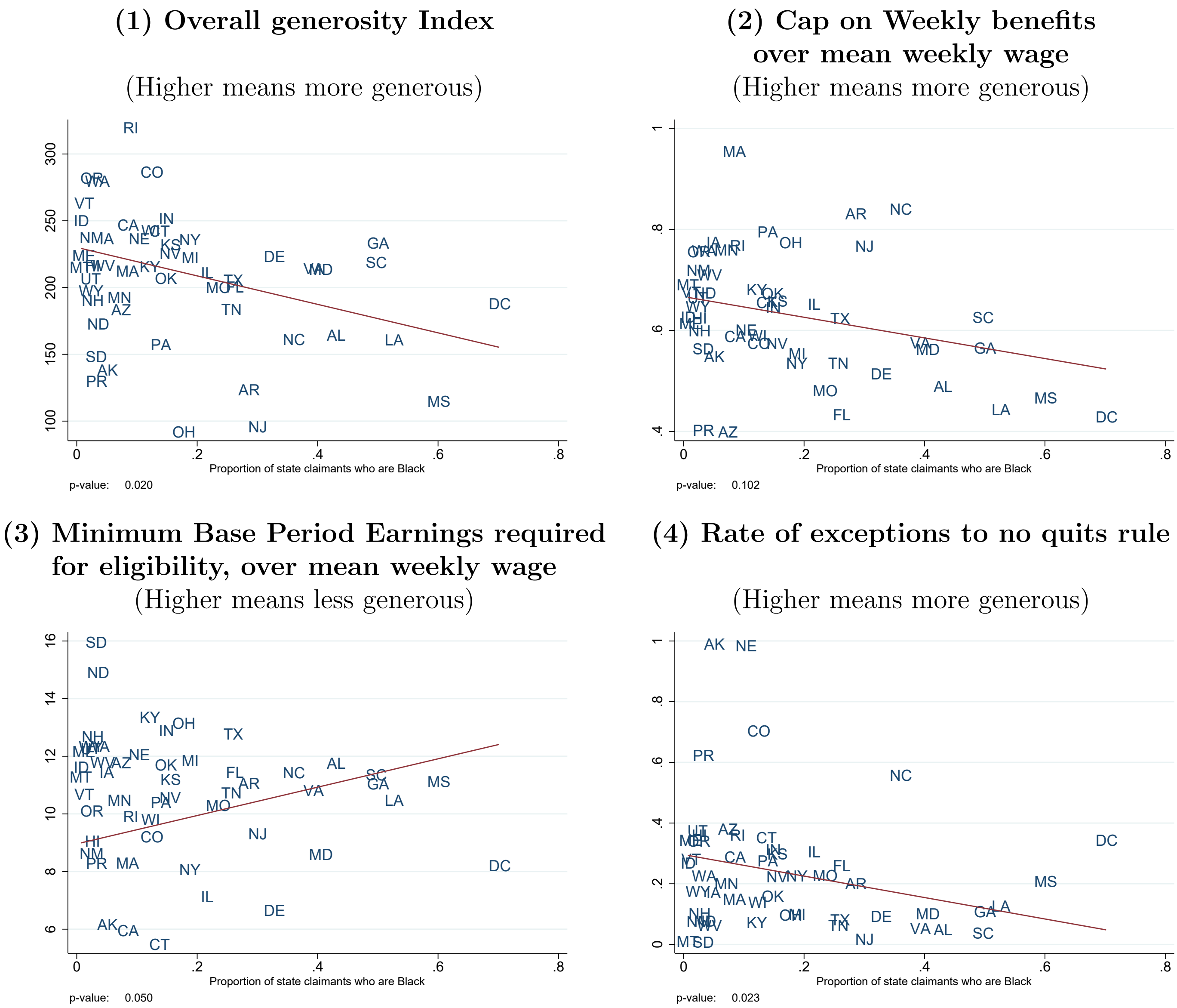


Proportion of state claimants who are Black



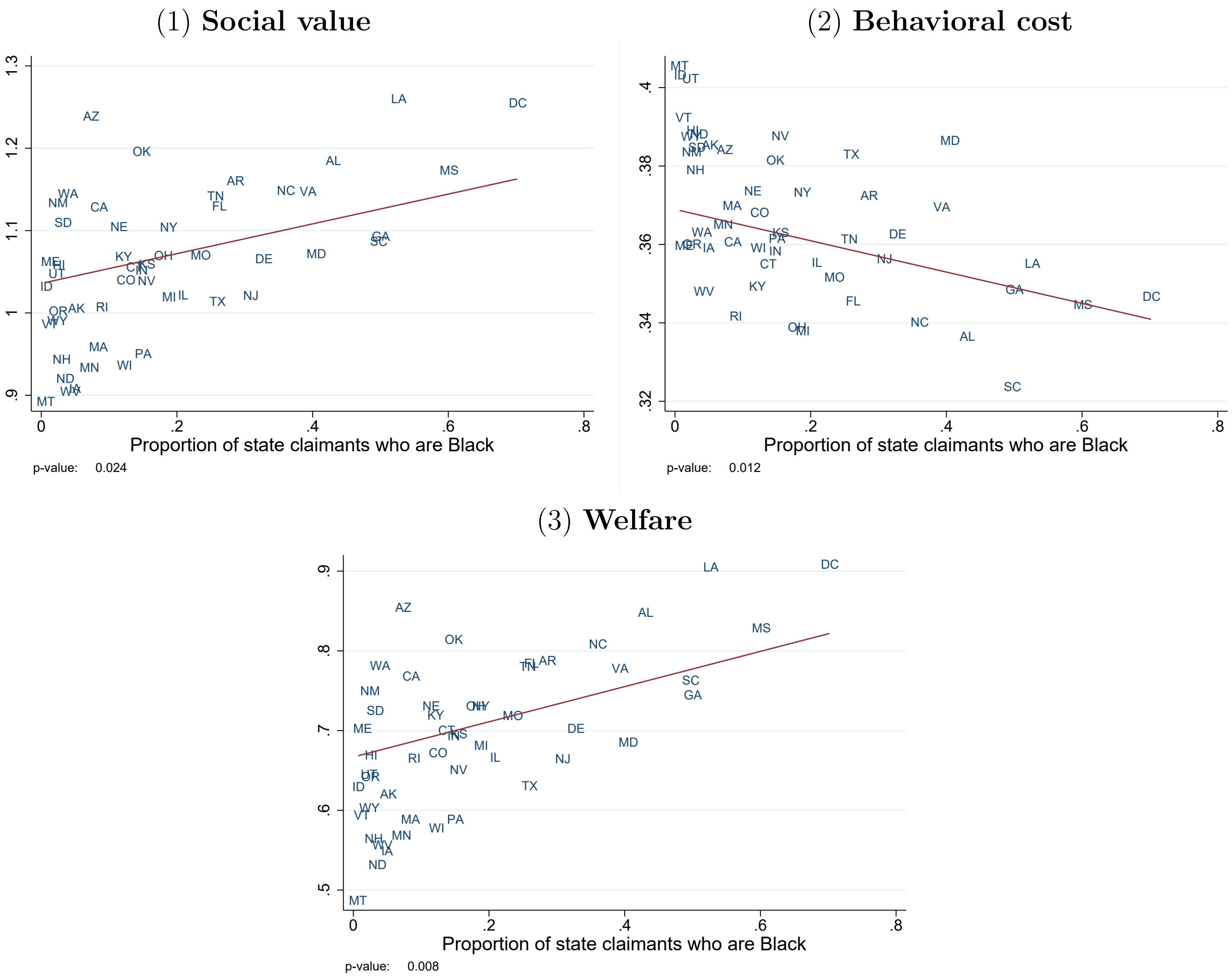
Notes: These two maps illustrate the negative correlation between state generosity in their UI rules, and their proportion of Black UI claimants. The first map represents the level of the statutory cap on the Weekly Benefit Amount according to the rule in each U.S. state, over the average weekly wage 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



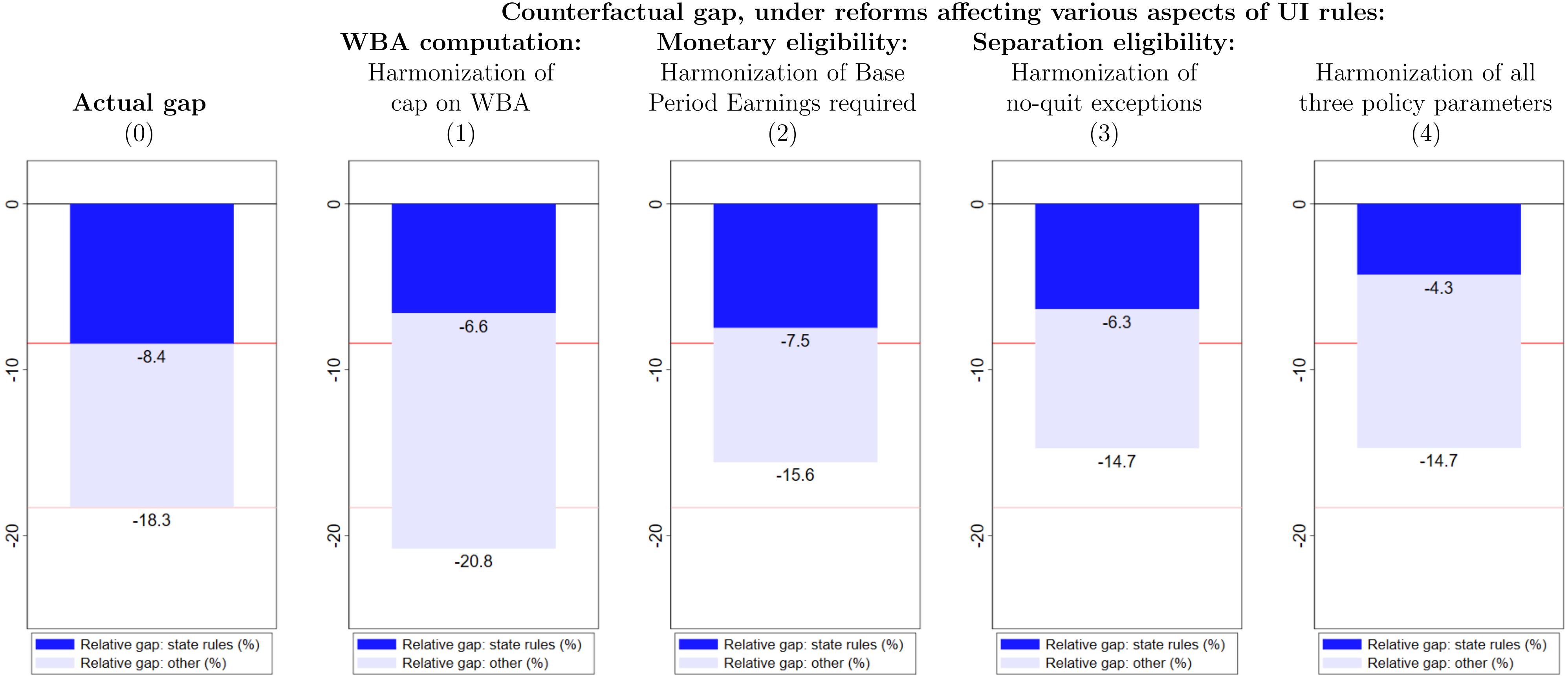
Notes: This Figure presents the correlation of state rule generosity and the share of claimants in the state who are Black. We measure state generosity using an index summarizing all dimensions of state rules, in Panel (1) (see Section 5.3); the statutory maximum level of weekly benefits relative to 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



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.

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

	Flow			Stock	
Variable	New claimants (BAM) (1)	New paid claimants (BAM) (2)	New unemployed (CPS) (3)	All paid claimants (BAM) (4)	All unemployed (CPS) (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 4.1 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 4.2 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 4.1 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.

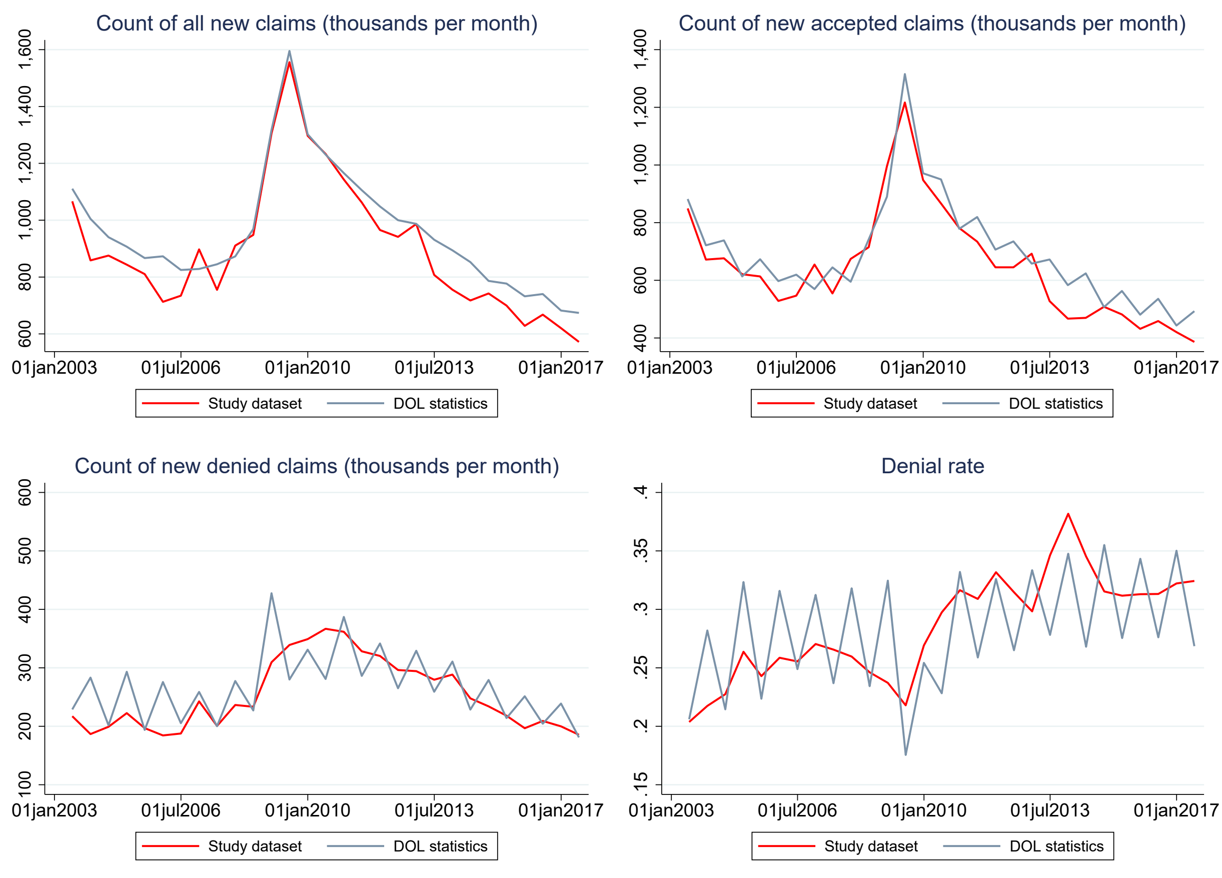
ONLINE APPENDIX

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, and the denial rate among new claims. Statistics for similar measures are available by quarter

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.

and state in the DOL table ETA 5159. 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").[17] 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 (O'Leary, Spriggs, and Wandner, 2021), so in columns (3) and (4) we remove state-years where more than 5 percent of benefit-weeks in the ETA 203 data were missing race. These adjusted samples also suggest highly similar composition along demographic dimensions.

A.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

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

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).

A.3 Measures of UI claiming rates, using BAM and CPS data

What is the fraction of new unemployed people who claim UI, and who receive UI? Although these are crucial questions, these fractions have been difficult to measure. In our case, the BAM data provide reliable estimates of the national counts of applicants and recipients across demographic groups, as in Table 1 (col (1), (2) and (4)). However, it is difficult to exactly measure the appropriate denominator for calculating a claiming rate. Here, we present some tentative measures of claiming and recipiency rates that we build by approximating the denominator using the CPS data. Although these ratios obtained from the combination of the BAM and the CPS data offer natural benchmarks, they should be interpreted with caution, given the potential measurement errors. In particular, we note that demographic categories are constructed differently in the BAM and the CPS, which could bias cross-group comparisons. In particular, demographic variables in the CPS are filled using imputation methods when respondents skipped the question or refused to answer (exploiting answers in other waves or from other household members in particular).[18] There is no such imputation in the BAM data and race is hence missing for 6% of claimants. With these caveats in mind, we present in this section the various ratios we constructed and discuss how they relate to other measures in the literature.

First, we measure the fraction of weeks of unemployment with paid UI benefits. This is the ratio of the count of all paid weekly claims in the BAM data each year over the count of workers who were unemployed in each week of the year in the CPS. More specifically, we take the stock of unemployed (excluding new entrants on the labor market) in the survey week of the monthly CPS multiplied by four. This measure is comparable to the UI recipiency rate produced by the US Department of Labor (e.g., see O'Leary, Spriggs, and Wandner (2022) Figure 10). Table A.2 shows that workers receive UI during about 28% of the weeks they spend in unemployment overall (col (1), line (i)). Black workers receive UI for only 23% of the weeks spent in unemployment (col (2), line (i)), and Black *or* Hispanic workers 24% (col (4), line (i)).

Second, we measure the claiming rate by taking the ratio of the count of new claimants over the count of new unemployed people (excluding new entrants on the labor market). Similarly, we build a UI receipt rate by taking the ratio of the count of new *paid* claimants over the count of new unemployed people. Note that while the ratio presented in line (i) measured the fraction of unemployed workers who receive UI at each given week of their

[18] See `https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/imputation-of-unreported-data-items.html`

unemployment spell, the UI receipt rate measures the fraction of unemployed workers who receive UI at least once during their unemployment spell. This claiming rate hence measures a somewhat similar object as the retrospective questions on past UI claim or UI receipt in the CPS UI-Non Filer Supplement (see e.g., Gould-Werth and Shaefer (2012)). We see that about 28% of workers who become unemployed receive UI at some point (col (1), line (ii)). This fraction is actually fairly similar for Black and White workers (col (2) and (3), line (ii)): indeed, a larger fraction of Black workers who become unemployed claim UI (47% of Black workers vs 35% of White workers, line (iii)), but a smaller fraction of Black claimants receive UI (61% of Black claimants vs 74% of White claimants, line (iv)).

The differences in the claiming rates of Black and White new unemployed workers measured in line (iii) reflect in part the different duration that Black and White workers spend in unemployment. A much larger fraction of White unemployed workers transition out of unemployment quickly, and workers might not claim for UI when they have another job lined up. Therefore, we also present two alternative definitions of claiming and receipt rates in lines (v) and (vi), where we take as a denominator the count of unemployed workers in their second month of unemployment. We hence leave out individuals who transition back to employment in less than one month. These measures suggest that among workers who stay unemployed at least 1 month, about 77% claim UI and 54% receive UI at some point. With these measures, Black unemployed workers still appear to apply a bit more frequently for UI (80% for Black unemployed workers vs 71% for White ones, line (vi)), but they receive UI less often (48% for Black unemployed workers vs 53% for White ones, line (v)). These rates of UI receipt might be more comparable to the measures built by Kuka and Stuart (2021) using the monthly labor market status reported in the SIPP.

Finally, it is important to note the differences between our definition of the claiming and receipt rates and other ratios discussed in the literature. In prior work, researchers have often computed a measure of the "take-up" rate, i.e. the ratio of UI recipients over unemployed workers who are (likely) eligible. For instance, Anderson and Meyer (1997) estimate an average take-up rate of 39% in 6 U.S. states during 1979-1983, Lachowska, Sorkin, and Woodbury estimate an average take-up rate around 45% in the state of Washington in 2005-2013. In this paper, we take a complementary approach: we do not restrict the denominator to the subsample of unemployed who are (likely) eligible, as we are precisely interested in how eligibility rules might affect UI recipiency. Our approach hence does not require us to determine which unemployed worker is (likely) eligible—which is difficult to accurately measure.

Table A.2: Measures of UI claiming and receipt rates, based on BAM and CPS data

Variable	(1) All	(2) Black	(3) White	(4) Black or Hispanic	(5) White non-Hispanic
(i) Fraction of weeks of unemployment with received UI	0.28	0.23	0.29	0.24	0.31
	(0.08)	(0.06)	(0.07)	(0.06)	(0.07)
(iii) Fraction of newly unemployed who file an initial UI claim and received UI	0.28	0.28	0.26	0.24	0.29
	(0.07)	(0.07)	(0.05)	(0.05)	(0.06)
(ii) Fraction of newly unemployed who file an initial UI claim	0.40	0.47	0.35	0.38	0.39
	(0.12)	(0.11)	(0.07)	(0.07)	(0.07)
(vi) Fraction of initial UI claims that are approved	0.70	0.61	0.74	0.64	0.75
	(0.10)	(0.09)	(0.08)	(0.09)	(0.07)
(v) Fraction of 1-month unemployed who file an UI initial claim and received UI	0.54	0.48	0.53	0.47	0.58
	(0.12)	(0.09)	(0.09)	(0.07)	(0.09)
(iv) Fraction of 1-month unemployed who file an UI initial claim	0.77	0.80	0.71	0.74	0.78
	(0.17)	(0.15)	(0.09)	(0.10)	(0.09)

Notes: This table presents various measures of UI receipt rate and claiming rate, using BAM data and the monthly Current Population Survey (CPS) for all the 50 U.S. states and the District of Columbia, for the period 2002-2017. We exclude new-entrants in the labor market from all the unemployed workers samples considered. We first present the ratios for all the population (col (1)), and then separately for different groups: col (2) and (3) consider separately Black and White workers (irrespective of their ethnicity) ; while col (4) and (5) consider separately Black or Hispanic and White non-Hispanic workers.

B Decomposition of the racial gap in UI

Using the same notation as in Section 4.1, 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 $\Delta = \mathbb{E}_b(Y)-\mathbb{E}_w(Y)$:

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

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):

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

C.2 Calibration

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

- We use publicly available information on the total UI tax collected (to measure τ) and the total benefits (to measure b) distributed by each state each year. We collect information on the maximum benefits duration (in weeks) for each state and each year from state UI laws (P).

- Then, for each state, we measure in the CPS the weekly exit rate out of unemployment (s) and the fraction of workers staying unemployed at least until the end of the maximum benefits duration (S_P).

- To capture the incomes of employed vs. unemployed workers, we measure the average earnings of employed workers and of workers who have been unemployed less than the maximum benefits duration in the ASEC, and assume that workers consume in each week their weekly income (yearly income converted weekly). Alternatively, we use the income measures from the Survey of Income and Program Participation (SIPP): because it is a monthly panel, it allows us to measure the within individual income drop around a change in employment status.

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

	Mean	Min	Max	Std.Dev.
A/ Statistics from various sources				
Total UI taxes in each state, year (millions)	1735.39	32.53	4892.30	1589.81
Total UI benefits in each state, year (millions)	1923.05	31.53	5851.34	1901.95
Maximum potential benefits duration (weeks)	25.56	22.26	30.00	1.36
Rate of benefits exhaustion	0.28	0.14	0.37	0.05
Exit rate out of unemployment	0.09	0.07	0.13	0.01
Drop in income at unemployment, over income during employment	0.59	0.49	0.71	0.04
Income of employed (weekly)	921.78	750.63	1346.01	91.41
Income of unemployed for less than max PBD (weekly)	380.40	270.20	502.98	51.22
B/ Calibrated parameters				
Risk aversion coefficient	2.00	2.00	2.00	0.00
Elasticity of unemployment duration wrt benefits	0.38	0.38	0.38	0.00
C/ Welfare calibration				
Social value calibration	1.07	0.89	1.26	0.08
Behavioral cost calibration	0.36	0.32	0.41	0.02
Welfare effect calibration	0.71	0.49	0.91	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.4 (1)). Results also remain similar if we compare the differences in income between unemployed and employed at the population level (using ASEC data), or for the same individuals (using SIPP data).

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.4 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. Let's assume N is the size of the population of UI recipients. Let's consider one random audit: the probability that this audit will concern individual i, who received unemployment benefits for a duration of B_i, is given by: $P_A(i) = \frac{B_i}{\sum_{j=1}^{N} B_j}$. It corresponds to how often individual i has appeared in the stock of UI recipients, relative to all the other recipients.

Next, the average duration before the audit for individual i is $\frac{B_i}{2}$, given that the probability to be audited is constant over the time of the unemployment insurance spell. We can use these two pieces to derive a simple relation between the expected unemployment duration at the time of the audit in the audited sample (A) and the expected duration of paid benefits for each unemployed worker:

$$\mathbb{E}(A) = \sum_{i=1}^{N} P_A(i)\frac{B_i}{2} = \sum_{i=1}^{N} \frac{B_i}{\sum_{j=1}^{N} B_j}\,\frac{B_i}{2} = \sum_{i=1}^{N} \frac{B_i^2}{2\sum_{j=1}^{N} B_j} = \frac{\mathbb{E}(B^2)}{2\,\mathbb{E}(B)}.$$

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

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

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:

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

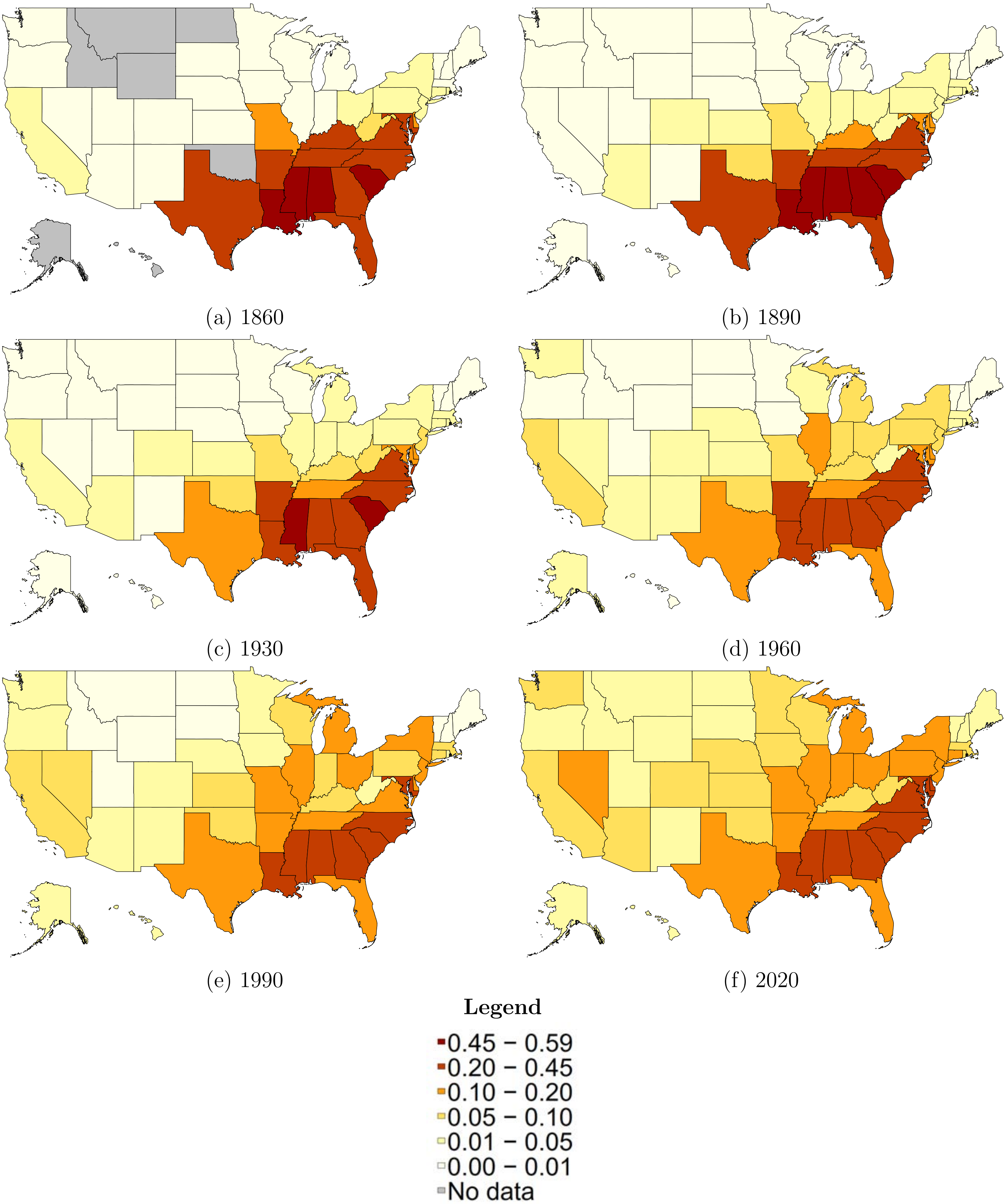
D Additional Tables and Figures

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 5.3). All earnings variable are normalized by the average prior wage earned by claimants in the state, to account for differences in price levels across states. Note that all variables measure the generosity of UI rules to claimants except for two, which instead measure the strictness of the rules: the proportion of recipients at Max WBA, and the min required BPE for eligibility. In the 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

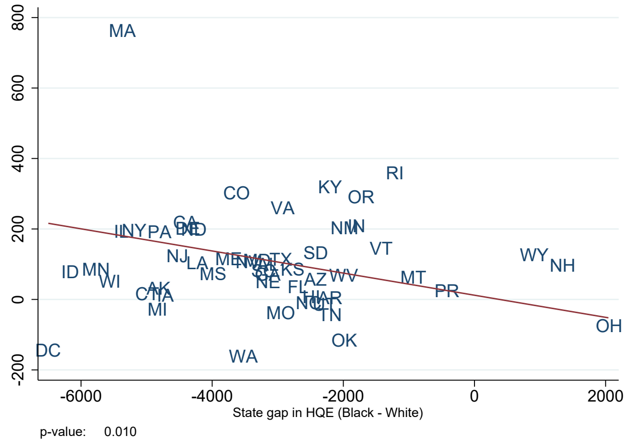
(f) 2020

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

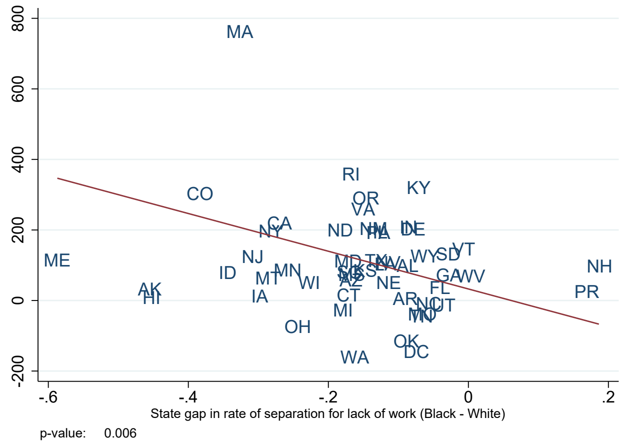
(A) State premium on work history &
State racial gap in index for work history

(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 the Index of overall generosity (see Section 5.3). Each panel presents a specific measure of the gap in work history characteristics in the x-axis: an index for 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). 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
	(3.099)	(0.004)	(0.006)	(3.802)	(0.005)
(i) Explained by State Rule differences	-35.829***	-0.038***	-0.084***	-13.197***	-0.014***
	(3.611)	(0.006)	(0.011)	(1.472)	(0.002)
(ii) Explained by Work History differences	-64.451***	-0.037***	-0.089***	-52.551***	0.020***
	(3.047)	(0.005)	(0.008)	(3.429)	(0.005)
(iii) Unexplained	7.971**	0.009	0.031**	-0.605	-0.003
	(3.839)	(0.008)	(0.012)	(1.543)	(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 %)	-13.0	-10.6	-11.1	-3.6	-3.0
(ii) relative to White mean (in %)	-23.5	-10.3	-11.8	-14.5	4.3
(iii) relative to White mean (in %)	2.9	2.6	4.2	-0.2	-0.7
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 consider that states change their UI regime when they implement large changes (by more than a 10%) in their cap on the weekly benefits amount: we identify 88 state$\times$UI regimes. We estimate a specific set of UI-rule parameters for each state$\times$UI regime, and then implement the decomposition.

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 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 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.

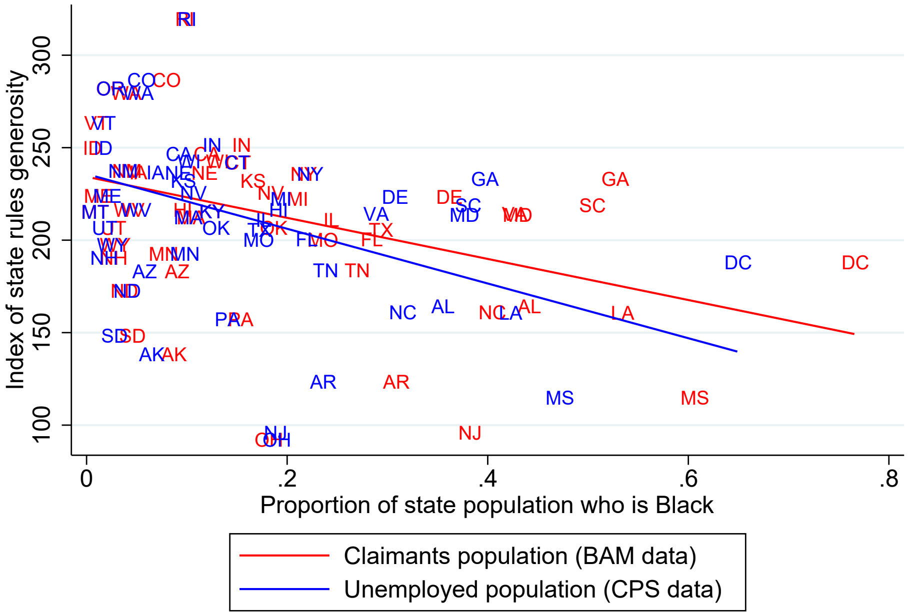
Table D.7: Gaps in UI generosity: Black or Hispanic vs White non-Hispanic

	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 4.1 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.

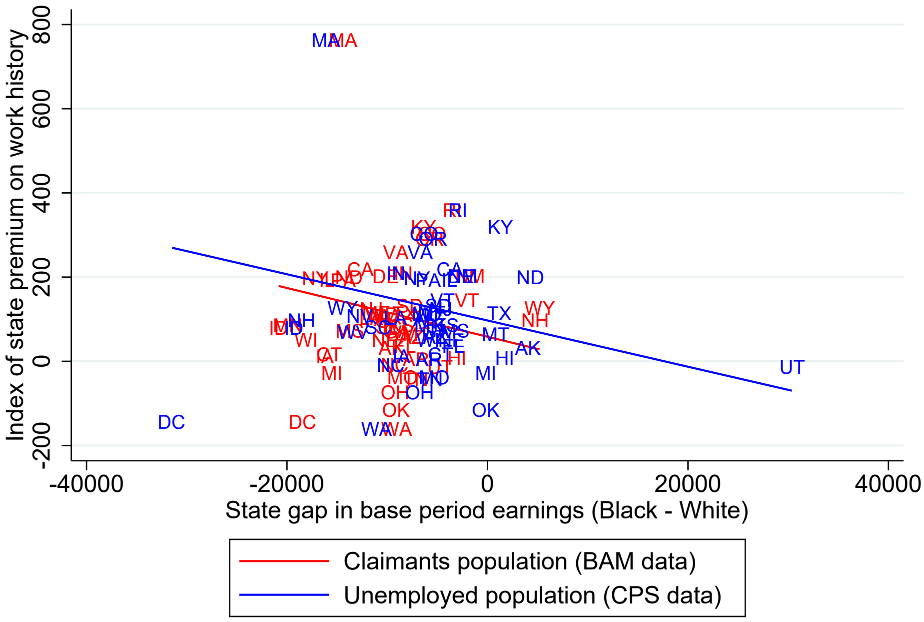
Figure D.3: Characteristics of Black and White workers across states, in the population of claimants and in the population of unemployed

(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

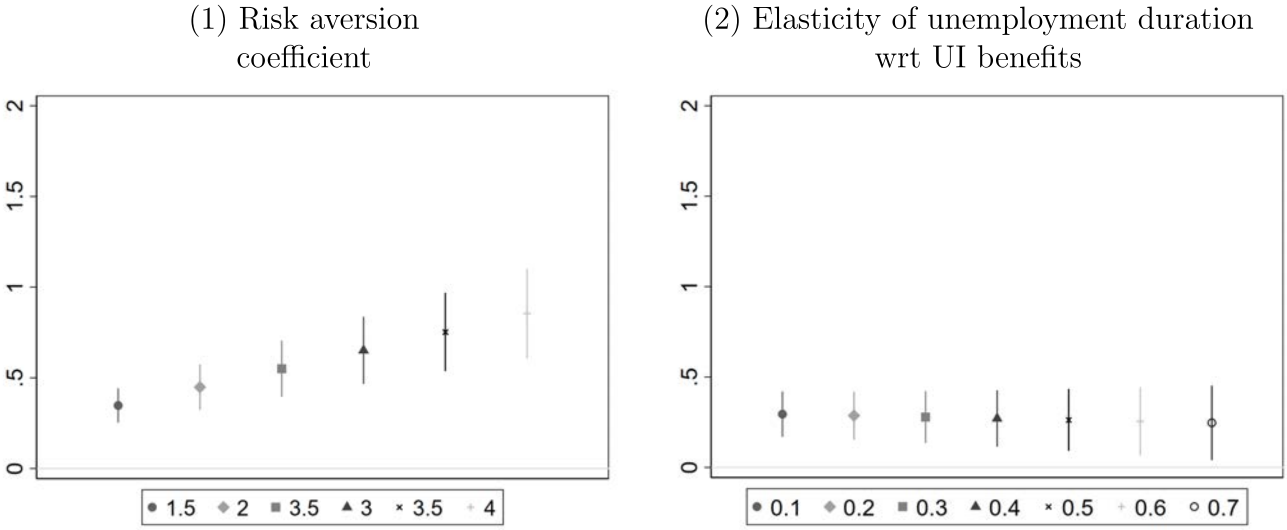
Notes: This table shows the decomposition of the actual and simulated racial gap in UI outcomes in various populations. In col (1) and (2), we consider population of BAM claimants, similar to our main analysis (Table 3). In columns (3) and (4) we consider the population of BAM claimants modified so that, 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).

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 3.2). 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.4: Correlation between the marginal welfare effect of a UI increase and the share of Black claimants, for alternative calibrations



Notes: These Figures present the marginal welfare effect of a UI, using the same calibration as that presented in Table 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).

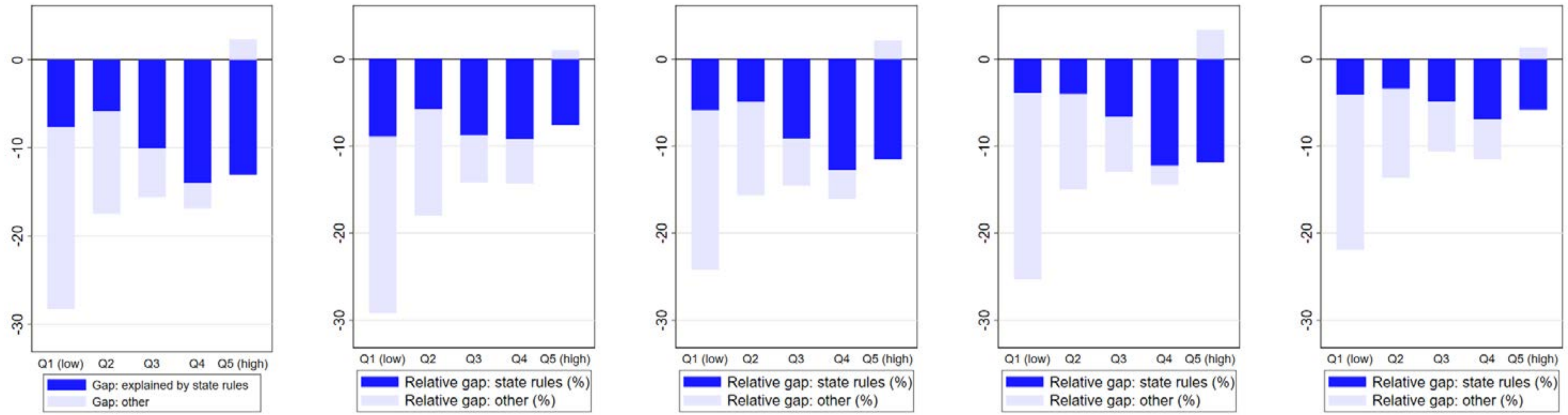
Figure D.5: Policy simulation

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.6: Heterogeneity in the actual and simulated racial gaps, across prior wage quintile

Counterfactual gap, under reforms affecting various aspects of UI rules:

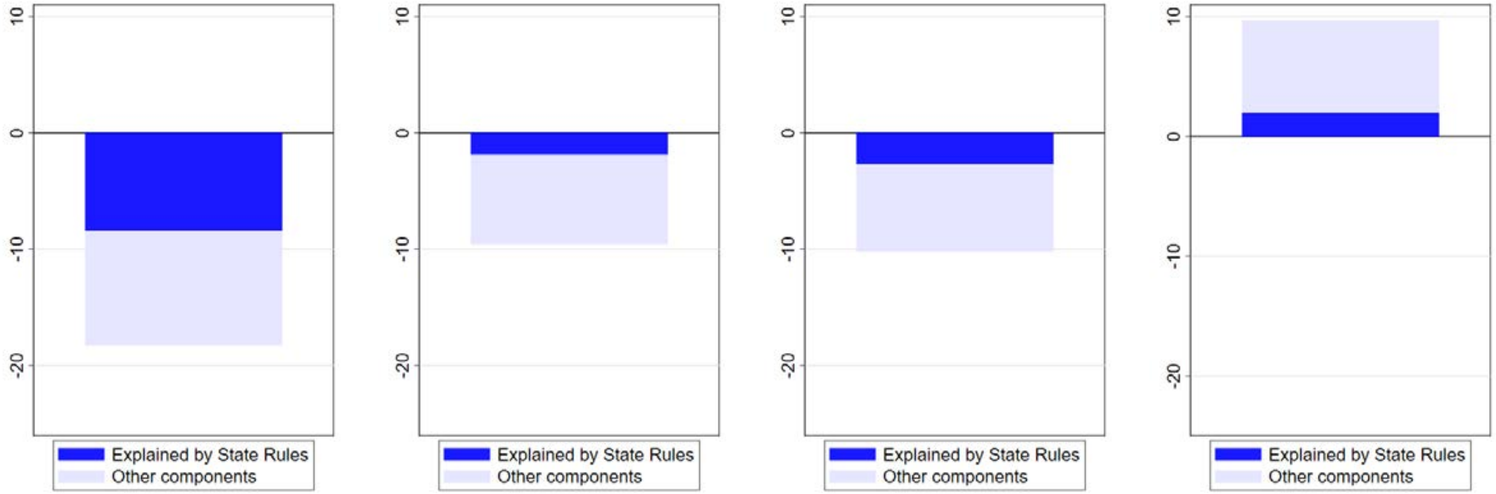
Actual gap (0)	**WBA computation:** Harmonization of cap on WBA (1)	**Monetary eligibility:** Harmonization of Base Period Earnings required (2)	**Separation eligibility:** Harmonization of no-quit exceptions (3)	**All:** Harmonization of all three policy parameters (4)



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.7: Gaps in replacement rate, between various demographic groups

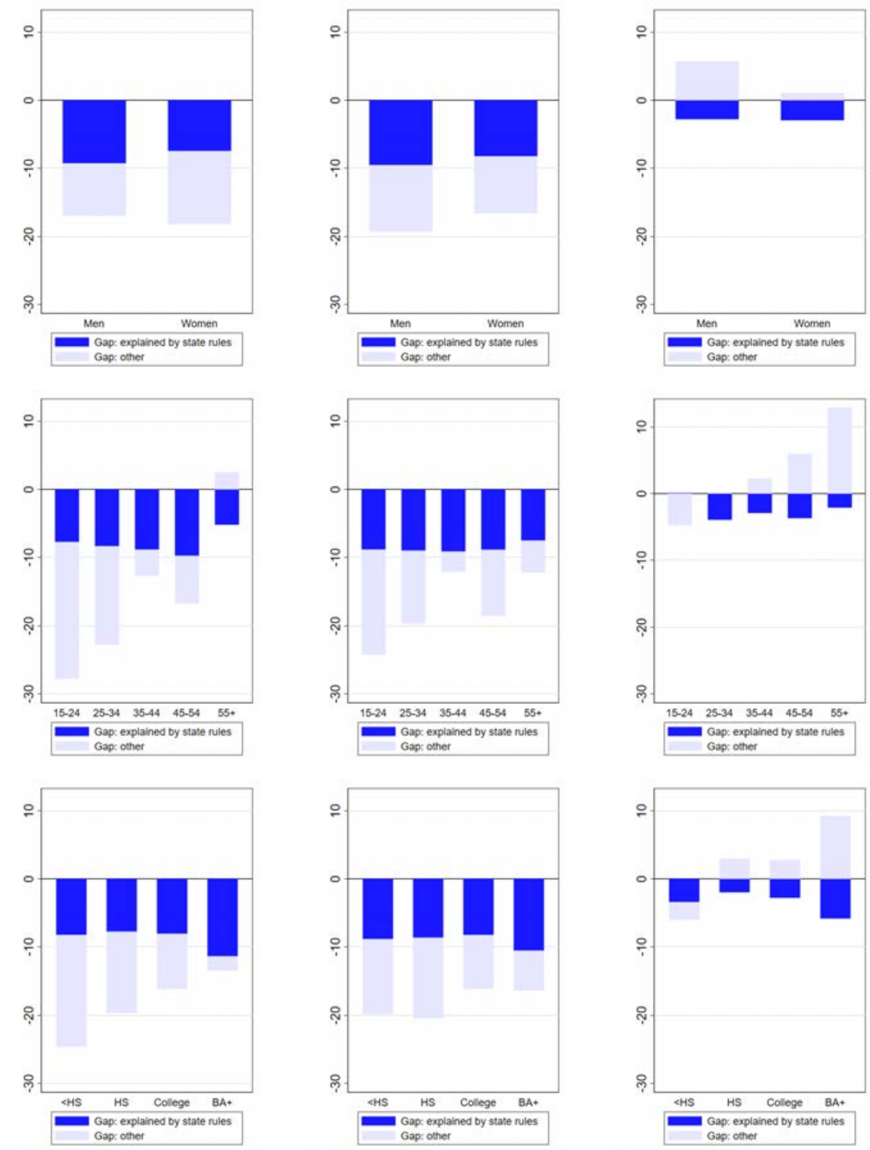
(1) Racial gap (2) Gender gap (3) Age gap (4) Education gap



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

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



Note: We present the Black-White gaps explained by state 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.