Technical Appendix

Project Name: Descriptive Study of Equity in the Distribution of the Emergency Rental Assistance Program

Date Finalized: 9/30/2022

Overview

The purpose of this document is to provide technical details on the analysis that are described neither in the analysis plan nor in the project abstract. These include decisions not pre-specified in the plan and additional results and analyses not reported in the main abstract. See the analysis plan and abstract for all other details.

Details and decisions not pre-specified in analysis plan

Hypothesis testing procedure

Between the publication of the analysis plan and the publication of the abstract for this project, OES published new guidance showing that the one-sample goodness of fit test originally outlined in the analysis plan might be inappropriately liberal in its rejection rates if used in this study, because the true attributes of both the population of recipient renters and the population of eligible renters are unknown—the one sample test initially envisioned treats the recipient proportions as known. When both samples' underlying distributions are unknown, as is the case here due to missing data, the guidance recommends a two-sample test of independence using a modified test statistic.

The classic two-sample test of independence derives a p-value by comparing the observed difference in the multinomial distributions of two samples to the cumulative density of the chi-square distribution, which gives the probability of observing a test statistic at least as extreme as the observed test statistic under the null that the observed samples are drawn independently from a common distribution. We conduct this analysis below in "Two Sample Chi-Square Test for Main Results". We do not report this test in the main analysis, however, as this test relies on a parametric approximation of the null distribution, which does not take account of the uncertainty introduced by the extrapolation and imputation and so is likely anti-conservative. It is unclear how and whether the bootstrap and imputation distributions of the chi-square test statistic can be used to conduct the two-sample test, because the sampling distribution of the test statistic OES derived through bootstrap and imputation does not provide the test statistic's distribution under the null of independence. We therefore cannot simply compare this distribution to the point estimate to derive p-values, as one could for example in the case of randomization inference under the sharp null of no effect for all units.

Description of the relevant unit of analysis

The analysis plan specified that estimates of demographic profiles for the recipient and eligible populations would pertain to heads of households. In fact, the mapping is not so simple with any of the datasets. ERA grantees were asked to collect data on the *primary applicant*, who likely in many but not in all cases would be the head of household. We subset the CPS data to anyone who could be a primary applicant: that includes adults who are the head of household themselves or the spouse, partner, roommate, or sibling of head of household. The ACS and Pulse datasets are subset to adults. The fact that ERA recipient data pertains to the demographics of primary applicants while the eligible renter data pertains to adults who *could have* been primary applicants means that differences between the demographics of the two groups could be due principally to who tends to become a primary applicant. For example, women being strongly represented among primary applicants may reflect the fact that women are more likely, even in an opposite-sex household, to apply for social benefits, rather than the fact that households headed by women were more likely to receive ERA.

Specification of weights for recipient demographic profile

Quarterly compliance reports submitted by grantees to Treasury contained information on the number of recipients falling into different demographic categories in a given quarter and for a given round of ERA. In many cases, however, we do not have reports for all quarters and rounds for a given grantee. Rather, we have a partial snapshot of the demographic profile for that grantee, taken from available reports in specific quarters and rounds of ERA. The question is how to aggregate these snapshots to the state level, given programs were of vastly different sizes. To weight grantee-level estimates up to the state, regional, and national levels, we must have some measure of program size. We take the total number of households assisted from the monthly ERA 1 and ERA 2 reports, as this is what Treasury uses to calculate the total program size. This number provides the weights used to aggregate demographics of recipients from the grantee to the state, regional, and national levels.

Measurement of eligibility: household size-adjusted median family income limits

Renters were only eligible for ERA if their household income fell below 80% of the HUD-defined median family income (MFI), often referred to as the area median income (AMI). For AMI definitions, we used HUD income limits from 2020. The FY 2020 MFIs and income limits are based on new metropolitan area definitions, defined by OMB using commuting relationships from the 2010 Decennial Census, as updated through 2017. We merged the household-size adjusted limits into the ACS, Pulse, and CPS microdata based on metropolitan area, and marked households as falling below the income eligibility threshold when their household income fell below the 80% MFI limit corresponding to the number of people in their household.

When merging MFI limiys to the CPS and ACS IPUMS datasets, the metropolitan area variables did not always provide a perfect match. Sometimes, this might just be due to small differences in notation. For example, "Youngstown-Warren-Boardman, OH" in the ACS data had to be recoded to "Youngstown-Warren-Boardman, OH-**PA**" to match the HUD MFI data. However, sometimes the underlying metropolitan area had changed shape between the collection of the ACS data and the definition of the MFI areas. In such cases, we matched to the closest equivalent. For example, "Boston-Cambridge-Quincy, MA-NH" in the ACS data was matched to the income limits for "Boston-Cambridge-Newton, MA-NH" in the FY 2020 MFI data.

Matching MFI data to the Pulse encountered two different challenges. First, the Census Pulse data only has metropolitan statistical identifiers for those units that were sampled from one of the 15 largest metro areas (see here). As a reminder, we make no assumption that the Census Pulse data is representative of the broader population – instead, we assume that we can use it to develop an *internally valid model* that predicts individuals' eligibility accurately in the ACS. As such, the most important thing is that the model is estimating eligibility correctly internally, not that it is representative. AMI limits are strongly dependent on which MSA one resides in, and predictive of eligibility. E.g., the same person earning 50K gross annually may be eligible for ERA in one area and not in another. As such, we subset the Pulse sample *only to those individuals sampled from one of the top 15 MSAs*, because we are able to safely say what their AMI is and therefore whether their income falls below it.

Second, income in the Pulse is defined categorically in increments of 10-25K. To be sure that anyone we are defining as eligible is indeed eligible, we code their "max possible income" (e.g., the top of their bracket) and mark them as eligible if this falls below 80% of the AMI. This might exclude some individuals who were eligible for ERA from the pool, though only those at the highest end of the income spectrum who, among the eligible, were therefore the least likely to need ERA based on income alone.

Measurement of eligibility: pandemic-induced financial hardship and housing instability

We adopt an inclusive approach to defining eligibility based on financial hardship and housing instability, where if a renter answers a question that indicates either financial hardship or housing instability, we consider them eligible if they also have qualifying household income. The logic is that those who experience housing instability likely also experienced or have a household member who experienced financial hardship, and vice versa.

When using the **Pulse**, any adult renter who had a qualifying household income is considered eligible for ERA if they also meet any of the following conditions (variable name in parentheses):

- (mortlmth) – they were not able to pay last month's rent on time
- (rentcur) – they are not caught up on rent
- (mortconf) – they do not have high confidence in being able to pay rent next month
- (evict) – they think it is very or somewhat likely they will be evicted in the next two months
- (wrkloss) – they or someone in their household experienced a loss of employment income since March 13, 2020
- (expctloss) – they expect they or someone in their household will experience a loss of employment income in the next 4 weeks due to the pandemic
- (rsnnowrk) – they are not working because they: did not want to be employed during the pandemic; are or were sick with coronavirus symptoms; are or were caring for someone with coronavirus symptoms; are or were caring for children not in school or daycare; are or were caring for an elderly person; their employer experienced a reduction in business due to the pandemic; they were laid off due to the pandemic; their employer closed temporarily due to the pandemic; they were concerned about getting or spreading the coronavirus
- (ui_apply) – they applied for unemployment insurance since March 13, 2020
- (tui_numper) – at least one person in the household has received unemployment insurance since March 13, 2020

When using the **CPS**, any adult renter who had a qualifying household income is considered eligible for ERA if they also meet any of the following conditions (variable name in parentheses):

- (covidunaw) - they were unable to work due to the pandemic at some time in the past four weeks
- (covidpaid) – they did not receive pay for hours not worked due to pandemic in the past four weeks
- (covidlook) – the pandemic prevented them from looking for work in the past four weeks
- (absent) – they were absent from work in the past week because they were laid off
- (empstat & whyunemp) – they were not part of the workforce last week because they were laid off or lost their job for some other reason

Missingness in predictors

There are two important prediction exercises in this project, each of which requires that we deal with missingness in the predictors. The first is the technique used to impute missing demographics for grantees who submitted transaction data but no quarterly compliance reports. For these grantees, we rely on ACS estimates to impute missing demographic categories. However, the ACS tract-level estimates do contain some missingness due to small samples and other issues. The second place where predictors are used is to develop the extrapolation models and post-stratification weights, using the variables described below in Selection of covariates in the extrapolation and poststratification models. In both cases, we use **mean imputation** to remove missingness from the predictors. Note that we use the pre-registered multiple imputation via chained equation (MICE) model to predict missing *demographic variables* in the recipient data, where we are unable to impute using the other means specified in the analysis plan.

Selection of covariates in the extrapolation and poststratification models

We link the ACS and Pulse microdata in two ways: first, we use a set of variables common to both surveys to predict those flagged as "likely eligible" or "likely ineligible" in the Pulse, and extrapolate these predictions to the ACS; second, we use variables common to both datasets to develop post-stratification weights for the Pulse that can be used to reweight the data so that, on those variables, it resembles the ACS.

For the extrapolation model, we simply use the full set of variables that we could identify as possible to code in a common manner across the two datasets. One variable present in both datasets that we do not include in the extrapolation or post-stratification is the variable that indicates which state individuals are in. With over fifty categories, this variable generates a very large model matrix in the extrapolation exercise that is too large for the computer's memory to handle. In the poststratification, the problems posed by the state variable are worsened because we need to compute sample proportions for every single combination of predictors, as explained in more detail below.

Here are the variables common to ACS and Pulse that we use in the extrapolation model:

1. oes_income_cut – categorical income variable to match Pulse categories
2. oes_race – four major racial categories recorded in Pulse
3. oes_sex_at_birth_female – binary indicator for sex
4. oes_hispanic_latino – binary indicator for ethnicity
5. oes_hhsize – count of number of persons in household
6. oes_married – binary indicator respondent currently married
7. oes_never_married – binary indicator respondent never married
8. oes_educ_no_hs_grad – binary indicator respondent never graduated high school
9. oes_educ_hs_grad_only – binary indicator respondent graduated high school but nothing further
10. oes_educ_undergrad – binary indicator respondent got undergraduate degree
11. oes_educ_grad – binary indicator respondent got graduate degree
12. oes_work_last_week – binary indicator respondent worked last week
13. oes_age – age
14. oes_insurance – binary indicator respondent has health insurance
15. region – categorical variable for census regions

When choosing variables for the post-stratification model, we cannot use all of the above variables, because post-stratification requires computing weights for each unique combination of the predictors. As the number and range of the predictor variables increases, the number of possible combinations very quickly reaches the trillions. This is particularly troublesome as the procedure requires dividing the proportion of the sample in cell c in one dataset by the corresponding proportion in the other. Without multiple trillions worth of uniformly-distributed data, many cells end up empty, which means we cannot compute weights.

As such, we narrow the post-stratification variables down to the following list:

1. As above:
    a. oes_race
    b. oes_sex_at_birth_female
    c. oes_hispanic_latino
    d. oes_never_married
    e. oes_educ_no_hs_grad
2. Recoded for simplicity:
    a. oes_age_over_45 – binary indicator respondent over 45 years old
    b. oes_hhsize_over_4 – binary indicator respondent household size greater than 4 people
    c. oes_income_over_75k – binary indicator respondent household income over 75K
    d. oes_educ_grad_or_undergrad – binary indicator respondent has undergrad or post-grad education

This simplification results in only four “problematic” cells, where we have some pulse respondents but no ACS respondents. We simply give these cells a proportion of .0000001 for the calculation of the weights.

Method for selecting extrapolation model

Aspects of the procedure for selecting an extrapolation model were included in the analysis plan and our procedure is consistent with those. However, certain steps were not specified so we describe the full procedure here:

1. Load cleaned ACS and Pulse data, which contains predictors listed above and sample weights, and where every Pulse respondent is labeled as likely ERA-ineligible or likely ERA-eligible
2. Split the Pulse data into 3/4 training data and 1/4 testing data
3. Fit four binary classification / regression models to the training data:
    1. Ridge regression (using glmnet)
    2. Lasso regression (using glmnet)
    3. Decision tree (using rpart)
    4. Random Forest (using xgboost)
4. Predict, in the training data, the continuous probability of eligibility for every respondent
5. For each model's predictions in the training data, use the pROC package to obtain the threshold for converting probabilities into classes that maximizes the True Positive rate while minimizing the False Positive rate
6. In the testing data:
    1. Use each model to predict the continuous probabilities as above

2. Use the thresholds obtained from the training data above to label testing observations as eligible and not eligible
3. Compute confusion matrices and obtain the recall and precision in the testing data for each model
4. Choose the model that maximizes recall

Smaller number of imputations and bootstraps for state-level results

The estimation of every combination of demographic variables, for every state, M x B = 200,000 times, results in a 44GB dataset of estimates that has over 141 million rows. At that size, standard GSA laptops cannot allocate enough memory to load or manipulate data. Therefore, in order to compute standard errors and confidence intervals at the state-level, we use M = 50 and B = 1000 (half of what was pre-registered). This likely means the variance estimates are somewhat conservative, but this is not of great concern given that we are interested in broad patterns, rather than in the statistical significance of individual state-level results.

Additional details on main results

Datasets used

Dataset	Unit of analysis and description	Comments on sample size, duplicates, and missingness
Monthly compliance reports for ERA1 and ERA2, for CY21 Q1-Q4	Reports submitted by grantees to Treasury on a monthly basis, detailing the total number of households who received ERA and the total amount spent.	Raw data for ERA1 contained 4454 rows, after deduplication there are 3518 monthly reports. Raw data for ERA2 contained 2759 rows, after deduplication there are 2266 monthly reports.
Quarterly compliance reports for ERA1 and ERA2, for CY21 Q1-Q4 and CY22 Q1	Reports submitted by grantees to Treasury on a quarterly basis, detailing the total number of households who received ERA, broken down by demographic categories.	Raw data starts with 45,932 rows, with several rows for every report. After cleaning and deduplication, we have 1,465 ERA round-quarter pairs for which we have demographic data. We are missing any demographic data for an estimated 12% of grantees.
Quarterly transaction reports for ERA1 and ERA2, for CY21 Q1-Q4	Payments made by grantees to household or landlord recipients of ERA, at the transaction level. Data contains amount, type, and location of payment.	OES estimates that we were able to successfully obtain latitude, longitude, and census tract identifiers for approximately 92.4% of the 5,526,584 unique

		transactions and 91.6% of the 1,406,015 unique addresses.
American Community Survey 2015-2019 Tract-Level Estimates	Unit of analysis is Census tract. 5-year estimates and shapefiles pulled using tidycensus in R.	OES kept only those census tracts matched to geocoded transactions
American Community Survey 2015-2019 IPUMS Microdata	Unit of analysis is individual adult renter. See here: Steven Ruggles, Sarah Flood, Ronald Goeken, Megan Schouweiler and Matthew Sobek. IPUMS USA: Version 12.0 [dataset]. Minneapolis, MN: IPUMS, 2022. https://doi.org/10.18128/D010.V12.0	IPUMS micro data data on 3,157,494 adult renters, of whom OES estimates 1,689,946 were likely eligible for ERA.
Current Population Survey IPUMS Microdata	Unit of analysis is individual adult renter. Monthly basic and March ASEC data for 2020 and 2021. See here: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren and Michael Westberry. Integrated Public Use Microdata Series, Current Population Survey: Version 9.0 [dataset]. Minneapolis, MN: IPUMS, 2021. https://doi.org/10.18128/D030.V9.0	Starting with 3,570,853 panel responses from 821,160 unique individuals, not all of whom answered questions on renter status and COVID impact, after deduplication, cleaning, and coding, OES was able to identify 1,497 unique individual renters estimated to be likely eligible for ERA.
Census Pulse Survey Microdata	Unit of analysis is individual adult renter. We use weeks 1-20, fielded prior to the rollout of ERA. See here: https://www.census.gov/programs-surveys/household-pulse-survey.html	Starting with 1,604,089 responses from 1,402,349 unique individuals, after deduplication, cleaning, and coding, OES was able to identify 123,034 unique individual renters estimated to be likely eligible for ERA.

Numerical tables for estimates derived from ACS

Category	Label	Recipient Estimate	Eligible Estimate	Difference	SE	Lower CI	Upper CI
ethnicity	% Hispanic or Latino	0.293	0.276	0.017	0.008	0.001	0.032
ethnicity	% not Hispanic or Latino	0.707	0.724	-0.017	0.008	-0.032	-0.001
gender	% Women	0.694	0.556	0.138	0.006	0.126	0.150
gender	% Men	0.301	0.444	-0.143	0.006	-0.155	-0.131
gender	% Non-Binary	0.005	-	-	-	-	-
income	% less than 30% of the AMI	0.644	0.362	0.282	0.009	0.264	0.300
income	% 30-50% of the AMI	0.220	0.303	-0.083	0.006	-0.095	-0.071
income	% 50-80% of the AMI	0.136	0.273	-0.137	0.005	-0.146	-0.128
race	% American Indian or Alaska Native	0.018	0.011	0.007	0.001	0.006	0.009
race	% Asian	0.025	0.056	-0.031	0.001	-0.034	-0.028
race	% Black or African American	0.460	0.235	0.225	0.006	0.212	0.237
race	% Native Hawaiian/Pacific Islander	0.016	0.004	0.012	0.000	0.011	0.013
race	% White	0.405	0.569	-0.164	0.004	-0.172	-0.157

Numerical tables for estimates derived from CPS

Category	Label	Recipient Estimate	Eligible Estimate	Difference	SE	Lower CI	Upper CI
ethnicity	% Hispanic or Latino	0.293	0.333	-0.040	0.015	-0.070	-0.010
ethnicity	% not Hispanic or Latino	0.707	0.667	0.040	0.015	0.010	0.070
gender	% Women	0.694	0.542	0.152	0.016	0.122	0.183
gender	% Men	0.301	0.458	-0.157	0.016	-0.188	-0.127
gender	% Non-Binary	0.005	-	-	-	-	-
income	% less than 30% of the AMI	0.644	0.318	0.326	0.017	0.293	0.358
income	% 30-50% of the AMI	0.220	0.323	-0.103	0.015	-0.132	-0.074
income	% 50-80% of the AMI	0.136	0.358	-0.222	0.014	-0.250	-0.194
race	% American Indian or Alaska Native	0.018	0.028	-0.010	0.005	-0.020	0.001
race	% Asian	0.025	0.076	-0.051	0.007	-0.065	-0.036
race	% Black or African American	0.460	0.255	0.205	0.014	0.177	0.233
race	% Native Hawaiian/Pacific Islander	0.016	0.008	0.008	0.003	0.002	0.015
race	% White	0.405	0.621	-0.216	0.014	-0.244	-0.188

Numerical tables for estimates derived from Pulse

We do not report Pulse-derived results in the main text. While broadly consistent with the ACS and CPS-derived results, some point estimates seem implausibly low (such as 12% of eligible renters having incomes less than 30% of AMI). The external validity of the eligible renter sample is harmed by the need to subset to the top 15 metropolitan areas (see Measurement of eligibility: household size-adjusted median family income limits). We have no reason to believe subsetting in this way compromises *internal* validity, however.

Category	Label	Recipient Estimate	Eligible Estimate	Difference	SE	Lower CI	Upper CI
ethnicity	% Hispanic or Latino	0.293	0.212	0.081	0.009	0.063	0.098
ethnicity	% not Hispanic or Latino	0.707	0.788	-0.081	0.009	-0.098	-0.063
gender	% Women	0.694	0.533	0.161	0.007	0.148	0.175
gender	% Men	0.301	0.467	-0.166	0.007	-0.180	-0.153
gender	% Non-Binary	0.005	0.000	0.005	0.001	0.003	0.007
income	% less than 30% of the AMI	0.644	0.123	0.521	0.009	0.503	0.539
income	% 30-50% of the AMI	0.220	0.258	-0.038	0.007	-0.051	-0.025
income	% 50-80% of the AMI	0.136	0.185	-0.049	0.005	-0.060	-0.038
race	% American Indian or Alaska Native	0.018	0.111	-0.092	0.004	-0.101	-0.084
race	% Asian	0.025	0.067	-0.041	0.002	-0.045	-0.038
race	% Black or African American	0.460	0.160	0.299	0.007	0.286	0.312
race	% Native Hawaiian/Pacific Islander	0.016	0.111	-0.095	0.004	-0.103	-0.086
race	% White	0.405	0.662	-0.257	0.005	-0.268	-0.247

Two Sample Chi-Square Test for Main Results

The original analysis plan for this study proposed to test for the statistical significance of divergences across a number of demographic characteristics using a one-sample multinomial test, with the following chi-square test statistic:

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \ , \tag{1}$$

where E denotes the number of people falling into a given demographic category in the recipient population and O the number of people in that category in the eligible population, for the i’th category. However, as mentioned above, this test assumes that E is known, which we cannot do in this context due to missing data in the recipient population. In this case, the test would tend to be overly liberal (high risk of false positives). The two-sample test statistic is more appropriate:

$$\chi^2 = \sum_{i=1}^{k} \frac{(K_1 R_i - K_2 S_i)^2}{R_i + S_i}; \text{ where } K_1 = \sum_{i=1}^{k} \sqrt{\frac{S_i}{R_i}} \text{ and } K_2 = \sum_{i=1}^{k} \sqrt{\frac{R_i}{S_i}}. \tag{2}$$

This new formulation takes into account uncertainty in the observed frequencies for sample 1, denoted by R, and the observed frequencies for sample 2, denoted by S. The values K 1 and 2 are normalizing constants that ensure that the frequencies for sample 1 are comparable with those in sample 2. Conceptually, this formulation compares the observed values in each sample in a given category to the average of the frequencies in a given category scaled to the size of each sample.

We present below the results of this test, applied at the level of the demographic categories into which respondents can be exclusively sorted (race and ethnicity cannot be included in the same test using this data, for example, as they are not exclusive and we do not have information on their intersection in the recipient data). We use the chisq.test function in R to conduct the test, relying on parametric approximation of the null distribution rather than bootstrapping and imputation. In the main results, the confidence intervals around many differences between eligible and recipient population characteristics, which we constructed using bootstrap and imputation standard errors, imply statistically significant differences at the characteristic level. Given that the two-sample chi-square test is generally going to be better-powered than any individual difference, since it borrows strength across the different characteristics, it should be no surprise that all of the demographic categories exhibit divergences between eligible and recipient demographic profiles that are highly unlikely to arise by chance. We reject the null hypothesis in all cases.

Category	Data Source used for Eligible Estimates	Chi-Square Test Statistic	p-value
Ethnicity	ACS	1624.029	< .001
Ethnicity	CPS	11.15391	< .001
Ethnicity x Income	ACS	313826.7	< .001
Ethnicity x Income	CPS	847.3544	< .001
Gender	ACS	112360	< .001
Gender	CPS	181.6305	< .001
Gender x Income	ACS	444945.2	< .001
Gender x Income	CPS	1195.947	< .001
Income	ACS	325524.3	< .001
Income	CPS	858.4646	< .001
Race	ACS	301102.1	< .001
Race	CPS	554.2008	< .001
Race x Income	ACS	528483.4	< .001
Race x Income	CPS	1748.149	< .001

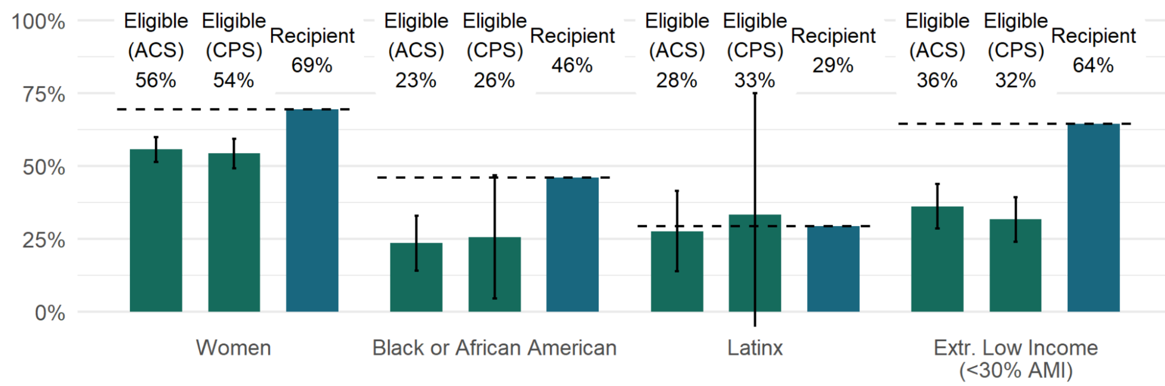
Main Results using Replicate Weights for Variance

As a robustness check, we re-estimate main results using the pre-computed replicate weights for the ACS and CPS surveys. We initially expected that bootstrap and imputation approaches to variance would be more conservative, as they incorporate variance both from sampling and from the estimation and imputation procedures. However, confidence intervals are wider when using replicate weights to approximate the variance in demographic estimates.

For major demographic categories, neither the substantive interpretation nor the statistical significance of the results is different from the main results reported above.

Figure 1: Main results for major demographic categories, using replicate weights for confidence interval estimation

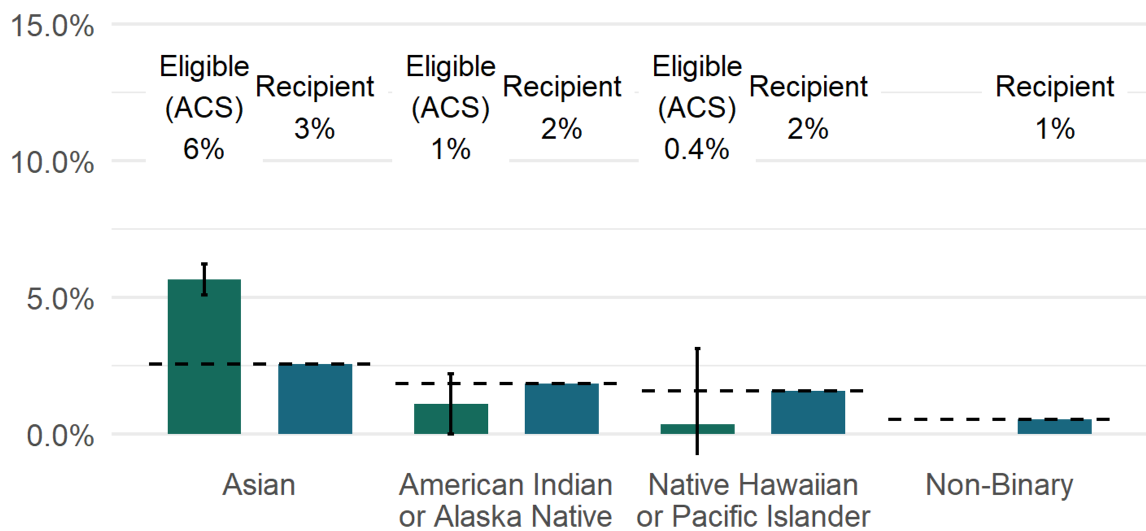
Note: height of bars represents estimated proportion of population falling into that demographic category for the ACS, CPS, and Treasury recipient data, respectively. Error bars represent 95% confidence intervals on the difference between the relevant eligible and recipient proportions, calculated using Census-produced replicate weights to produce imputation standard errors.



For Asian renters, the substantive interpretation and statistical significance of the results is not different from the main results reported above when using replicate weights to estimate variance. However, AIAN and NHPI overrepresentation is no longer statistically significant.

Figure 2: Main results for small demographic categories, using replicate weights for confidence interval estimation

Note: height of bars represents estimated proportion of population falling into that demographic category for the ACS and Treasury recipient data, respectively. Error bars represent 95% confidence intervals on the difference between the relevant eligible and recipient proportions, calculated using Census-produced replicate weights to produce imputation standard errors. We calculate proportions of smaller demographic groups using ACS data only, as sample sizes are too small in the CPS. We omit the "mixed race" category due to concerns over methodological differences in how it is coded. Data on American Indian or Alaska Native receipt pertains to non-Tribal government programs only, as Tribal governments were not required to report on the demographics of their recipients.

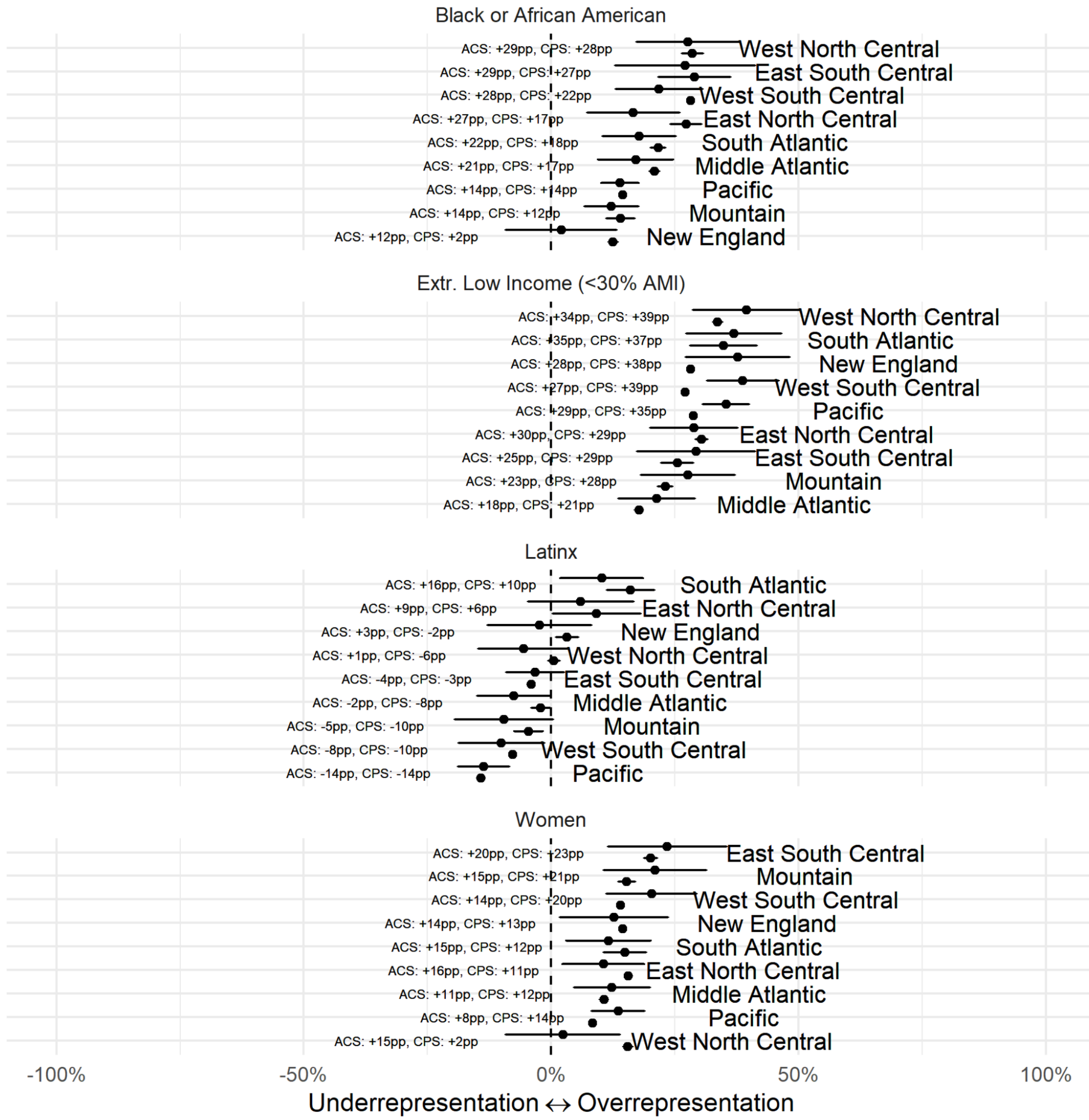


Additional results

Regional Variation

Figure 3: Regional variation

Points represent estimated difference between recipient and eligible population proportions. ACS and CPS used to estimate proportions of the eligible population.



State-Level Variation

Figure 4: Under- or Overrepresentation of Black renters by state

Note: points represent estimated difference between recipient and eligible population proportions. Estimates of eligible population demographic profile derive from ACS only.

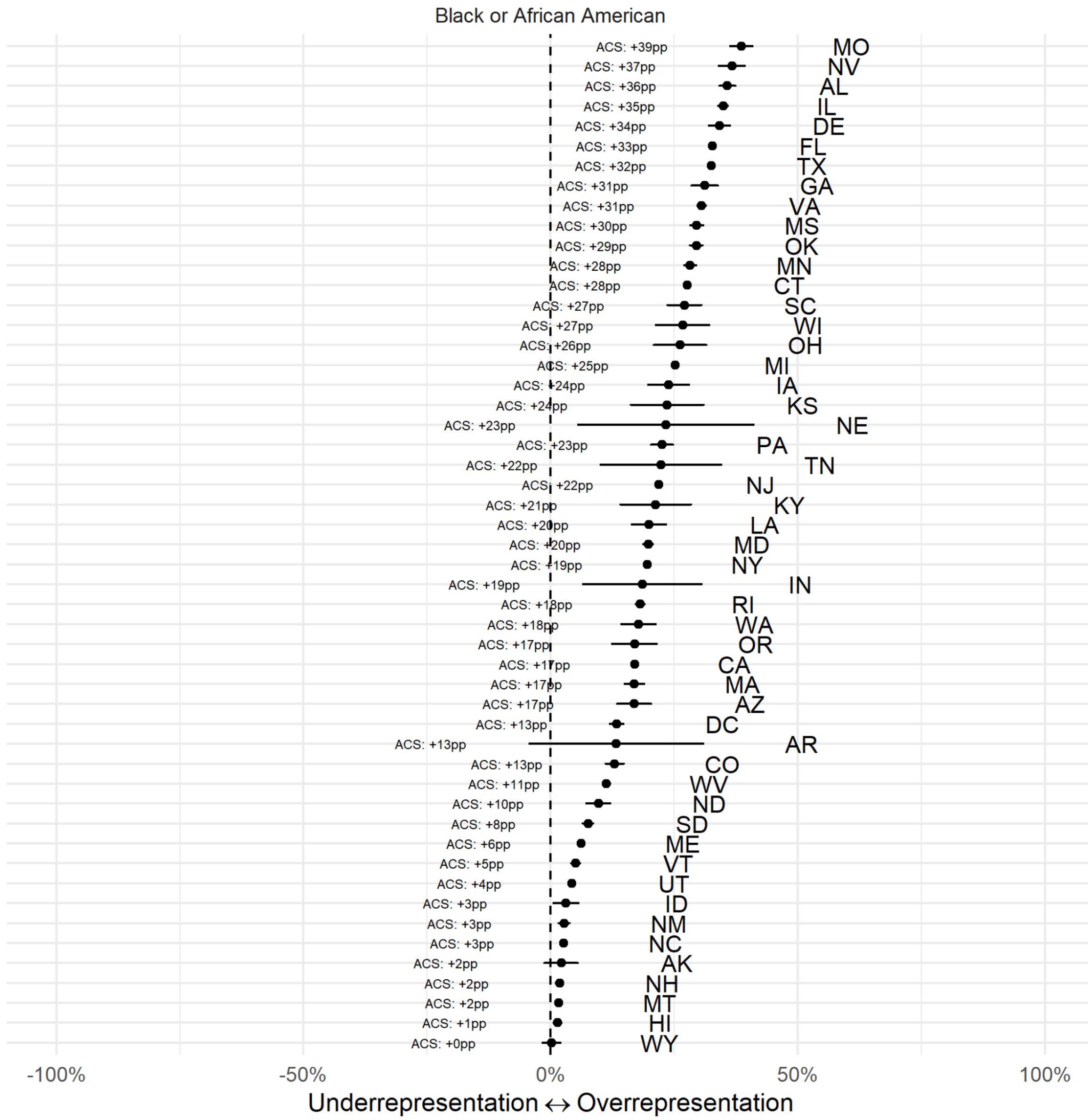


Figure 5: Under- or Overrepresentation of women renters by state

Note: points represent estimated difference between recipient and eligible population proportions. Estimates of eligible population demographic profile derive from ACS only.

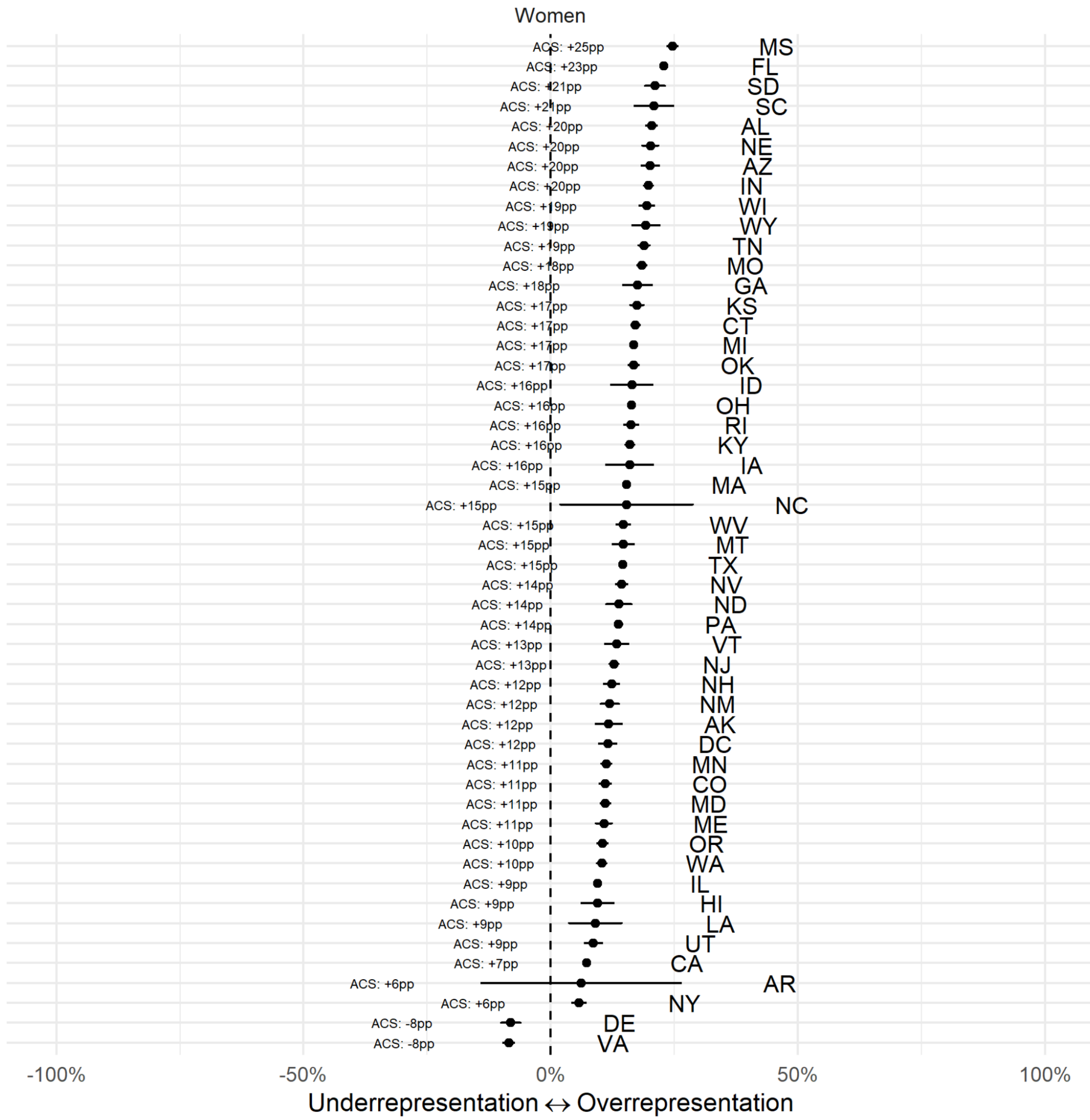


Figure 6: Under- or Overrepresentation of Latinx renters by state

Note: points represent estimated difference between recipient and eligible population proportions. Estimates of eligible population demographic profile derive from ACS only.

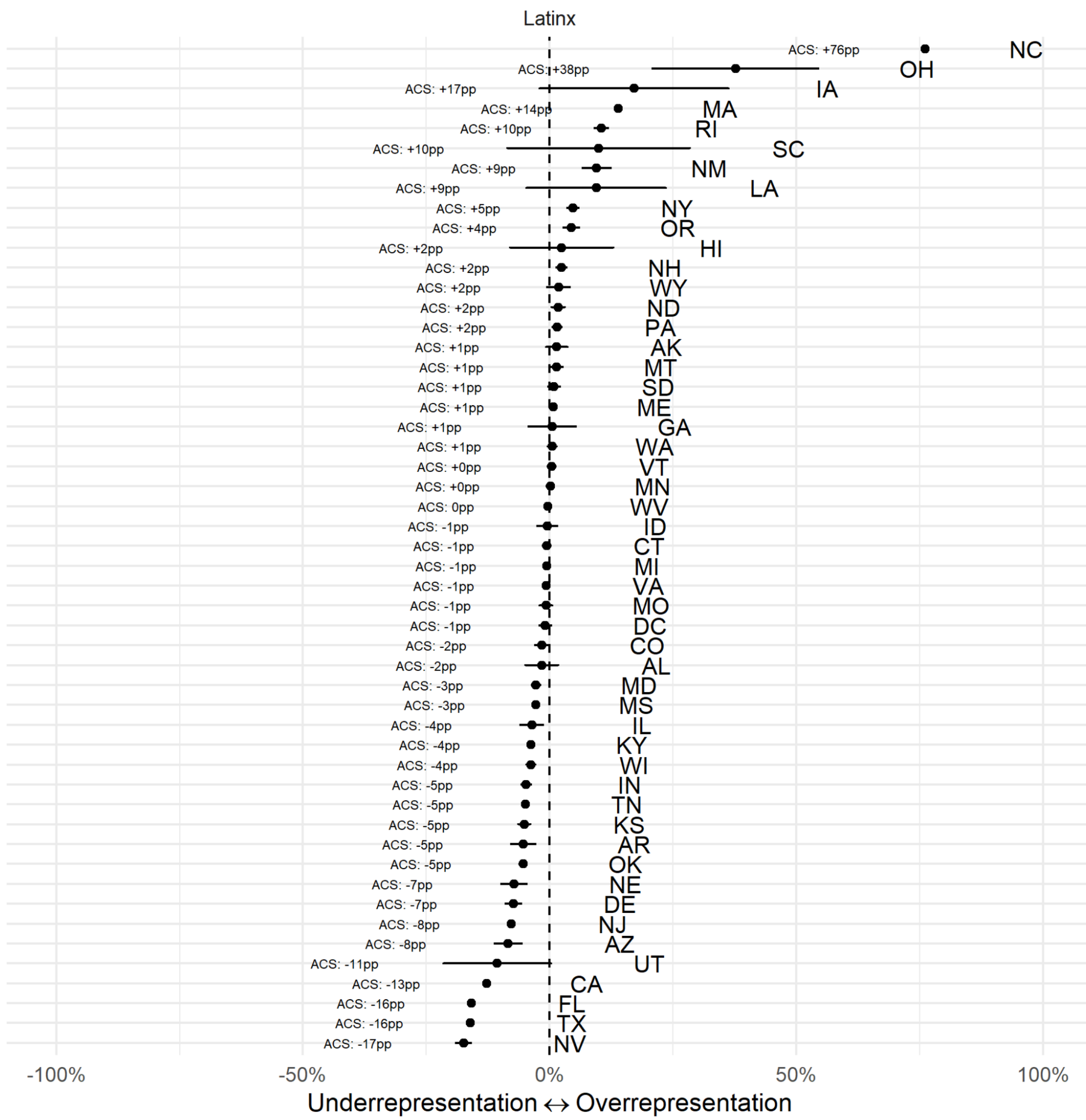
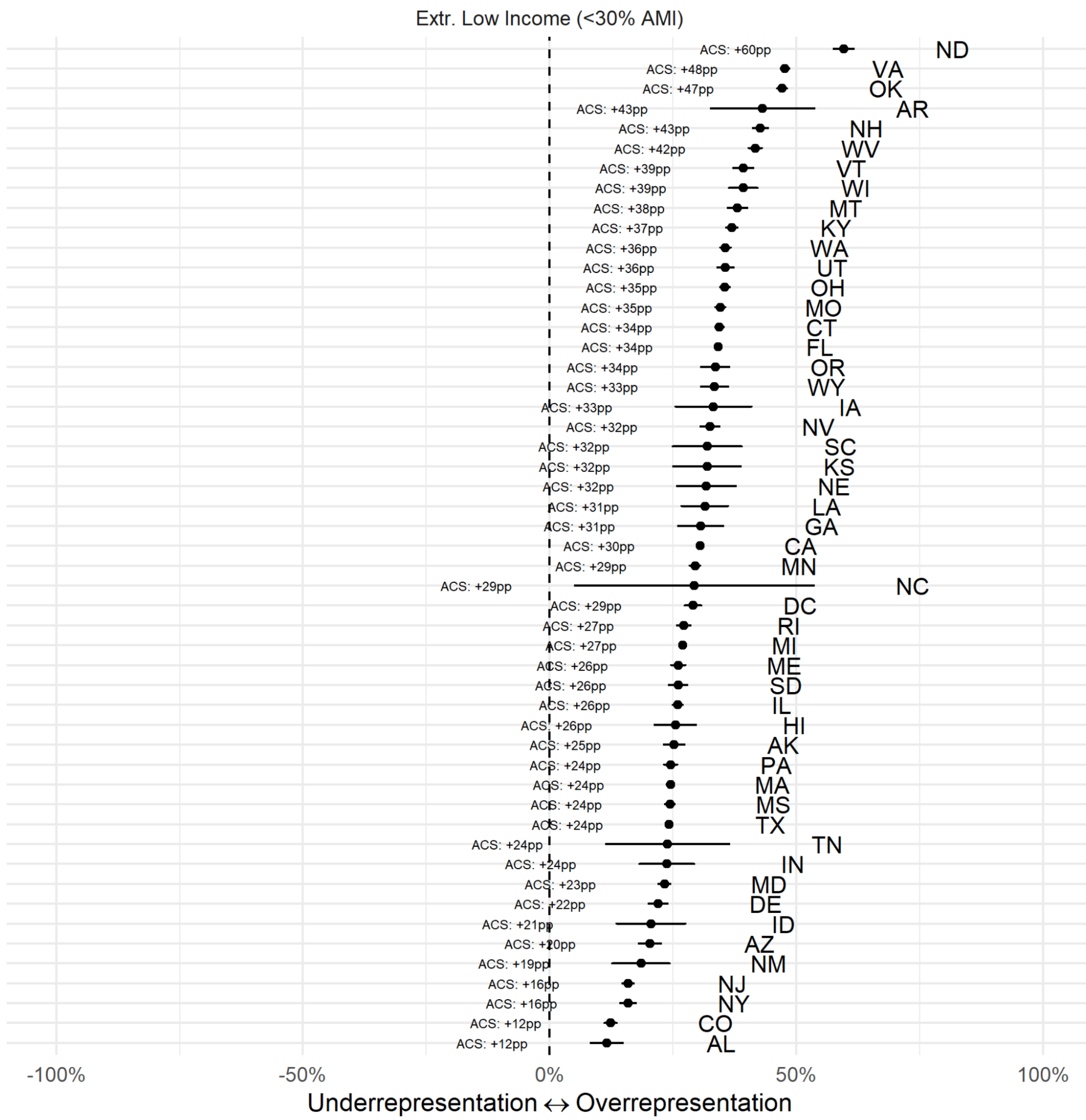


Figure 7: Under- or Overrepresentation of extremely low income renters by state

Note: points represent estimated difference between recipient and eligible population proportions. Estimates of eligible population demographic profile derive from ACS only.



Eligible versus Ineligible Renters

Eligible renters were more likely than eligible renters to be Black, and less likely to be White. There are no strong differences between the proportion of eligible and ineligible renters who identify as Asian, American Indian or Alaska Native, or Native Hawaiian or Pacific Islander.

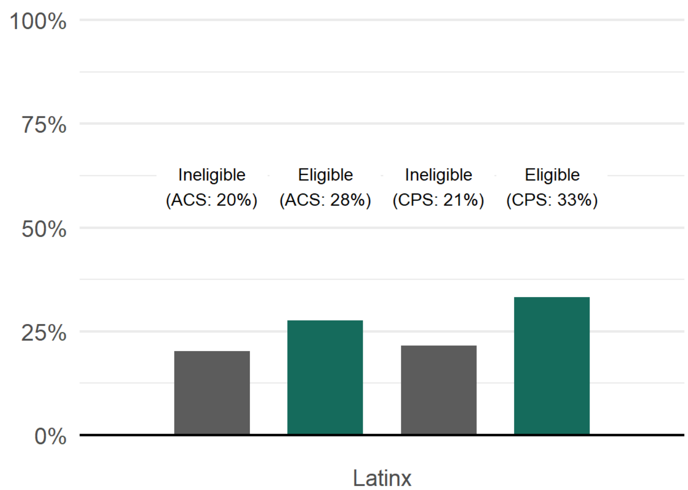
Figure 8: Eligible versus ineligible renters - Race

Note: height of bars represents proportion of renters predicted to be ERA-ineligible or ERA-eligible who fall into that demographic category, in the ACS and CPS, respectively.

Eligible renters were more likely than ineligible renters to be Latinx.

Figure 9: Eligible versus ineligible renters - Ethnicity

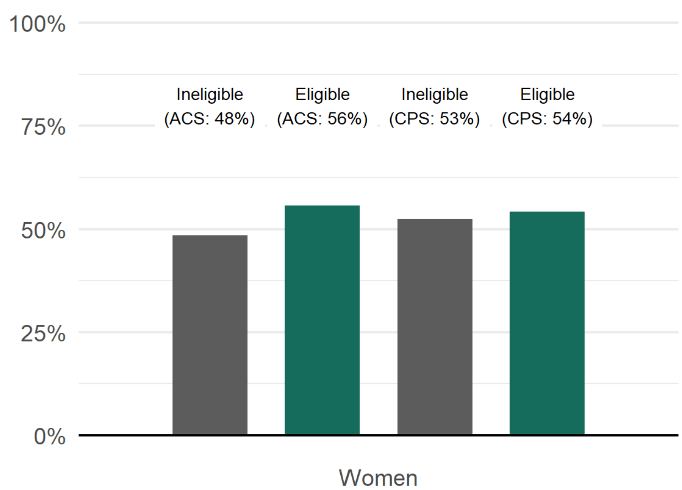
Note: height of bars represents proportion of renters predicted to be ERA-ineligible or ERA-eligible who fall into that demographic category, in the ACS and CPS, respectively.



Eligible renters were more likely than ineligible renters to be women. We do not know what proportion of eligible renters identified as non-binary.

Figure 10: Eligible versus ineligible renters - Gender

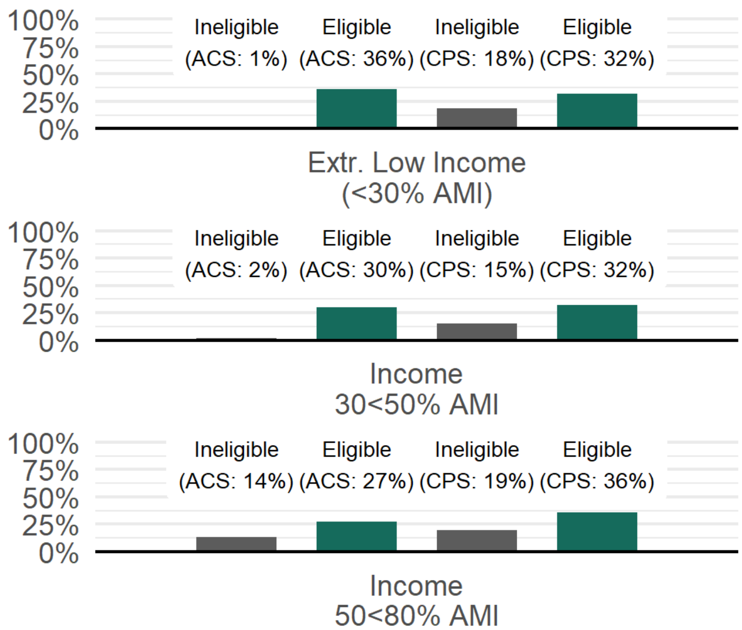
Note: height of bars represents proportion of renters predicted to be ERA-ineligible or ERA-eligible who fall into that demographic category, in the ACS and CPS, respectively.



No renters with an income above 80% of AMI were eligible, so the proportion of renters with incomes below 80% AMI are higher for eligible than ineligible renters across the board. The predictive model used to extrapolate to the ACS from the Pulse predicts that almost all individuals with an income below 50% of AMI were eligible. The CPS estimates predict some such renters were not eligible, however.

Figure 11: Eligible versus ineligible renters - Income

Note: height of bars represents proportion of renters predicted to be ERA-ineligible or ERA-eligible who fall into that demographic category, in the ACS and CPS, respectively.



Head of Household Gender

The main results estimate that 69% of *recipients* of ERA were women renters. Because the recipient data measures primary applicants and not all recipients, it is likely that some of these female primary applicants live in mixed gender households. This raises a concern that gendered division of labor in mixed gender households, and not overrepresentation of women-headed households, could be driving the results (i.e., that women in a mixed gender household take up the household task of filling the household's application for ERA).

We do not have information on the household structure of ERA recipients, and so we cannot adjust the recipient estimate. We can, however, go some way toward addressing this concern by looking at the household structures of those *eligible for* ERA and using this information to draw inferences about how severe this gendered division of labor would need to be in order to

The HHTYPE variable in the ACS IPUMS data classifies households as headed by a married couple, headed by a male or female head of household with an unmarried partner present, or headed by a solo male or female head of household. Table 1 subsets the ACS data to those predicted to be eligible for ERA, and shows the counts and proportions of eligible renters living in households that are headed by a married couple, a solo or partnered unmarried man, or a solo or partnered unmarried woman.

Table 1: Head of household gender among eligible renters

Note: Counts and proportions below are derived from the ACS, using the Pulse model to extrapolate eligibility as described above and the hhtype variable to code household structure. Estimates are weighted using person weights produced by Census.

	Household Type		
	Household headed by married couple	Household headed by man (solo or with partner)	Household headed by woman (solo or with partner)
All eligible renters	539,410 (35.8%)	309,344 (20.6%)	656,341 (43.6%)
Eligible renters with HH income <30% AMI	140,342 (24.8%)	124,781 (22.0%)	301,309 (53.2%)

If we are willing to assume a) that heads of households are primary applicants; and b) that these three different household structures — households headed by a married couple, households headed by a man only, and households headed by a woman only — apply for ERA at the same rate (more on this below), we can address the following question relatively simply: what proportion of households headed by married couples would need to have had women primary applicants in order to have 69% of primary applicants be women? Similarly, we can allow that households headed by a man where a woman may be present might also have had female primary applicants, and conduct a similar calculation.

Denoting the number of households headed by a solo or partnered man *m*, the number of households headed by a solo or partnered woman *w*, the number of households headed by a married couple *g*, and the proportion married couple-headed households who have women as primary applicants *p*, one simplified way of answering this question is to solve for p in the following expression: (g * p + w)/(m + w + x) = .69. Using this method implies that 71% of mixed gender households would have had to have female primary applicants in order to achieve the observed receipt rate, which is a very strong skew. Even under the most conservative assumptions, in which we allow that every single household headed by a man where a woman may have been present could have had a woman primary applicant, and assume that no households headed by women had men that applied to ERA, over half such households (55%) would have needed to have female primary applicants in order to reach the 69% receipt rate.

Moreover, looking at the eligible renters who had incomes below 30% of the AMI, represented on the bottom row of Table 1, we see that the assumption that different household structures applied at the same rate is also a conservative one. Recall that two-thirds of all ERA recipients fall into the very lowest income category, so that this is by far the predominant group of recipients. Among this strongly-overrepresented income group, the majority of all households — 53% — are headed by a woman. Finally, it is worth noting that overrepresentation of women renters is highest among this income group, in which the majority of households are headed by women, as depicted on Figure 12. Taken together, it is not unreasonable to conclude that overrepresentation of women renters is driven in strong part by high representation of women-headed households.

Figure 12: Representation of women eligible renters at differing income levels.

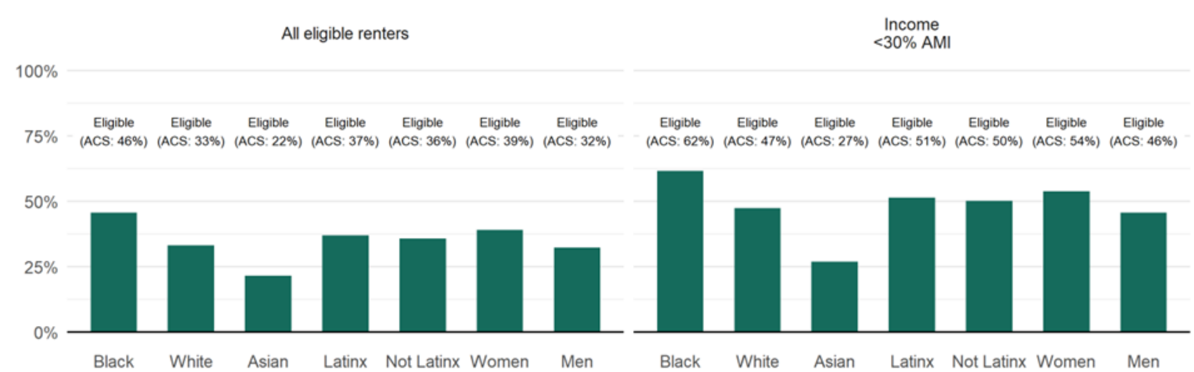
Note: height of bars represents estimated proportion of population falling into that demographic category for the ACS

Uptake of government benefits among renters predicted eligible for ERA

To contextualize the findings on over- and underrepresentation, it is helpful to consider rates of uptake of other government benefits among eligible renters belonging to different demographic groups. On Figure 13, we plot the proportion of eligible renters who, in their answers to the American Community Survey, reported that they receive food assistance, public health insurance, or public income assistance. The left plot shows uptake rates for different groups across all renters predicted to be eligible in the 2015-2019 ACS microdata. For example, the first bar indicates that 46% of renters predicted to be eligible for ERA who identify as "Black or African American" received food assistance, public health insurance, or public income assistance. The plot on the right shows these same estimates, subset to renters whose household incomes fall at or below 30% of the household size-adjusted area median income (see above for methodology). All estimates are derived from weighted averages that use the Census-provided person weights.

Figure 13: Proportion of renters predicted eligible for ERA receiving other forms of public assistance, by demographic group

Note: Height of bars represents the proportion of renters predicted to be eligible for ERA in the ACS, who report receiving federal or state food assistance, public health insurance, or public income assistance.



Recall that Black renters are overrepresented among ERA recipients at all income levels, whereas White renters are overrepresented only at the lowest income levels and Asian renters are underrepresented at all income levels. These findings are consistent with benefits uptake among other programs: among those with extremely low incomes, Black renters are much more likely to receive benefits from other government programs than White or Asian renters. For both Black and White renters, there is a stark contrast between, on the one hand, benefit receipt levels in general, and on the other hand, benefit receipt at the lowest levels of income: benefits receipt among Black and White renters with extremely low incomes is 16 and 14 percentage points higher, respectively. We see no such jump for Asian renters, however: receipt rates are only 5 percentage points higher among the extremely low income group when compared to the average ERA-eligible Asian renter. In other words, the evidence is consistent with generally low uptake among Asian renters. At extremely low income levels, Asian renters receive other government benefits at half the rate Black renters do, and at 60% the rate of White renters.

We see no evidence that ERA-eligible renters who are Latinx receive benefits at a higher or lower rate than other ethnic groups. Among those eligible renters with extremely low incomes, for example, the receipt rates for these two groups are 51% and 50%, respectively.

Finally, ERA-eligible women renters access other benefits at higher rates than their male counterparts (recall we are unable to measure non-binary gender identification in the ACS). Among all ERA-eligible renters, the rates of benefit uptake for women and men are 39% and 32%, respectively, while among those with extremely low incomes the gap is even larger, with women and men receiving benefits at a rate of 54% and 46%, respectively.