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Social Security Policy Design and Racial Wealth Disparities—Baseline Results

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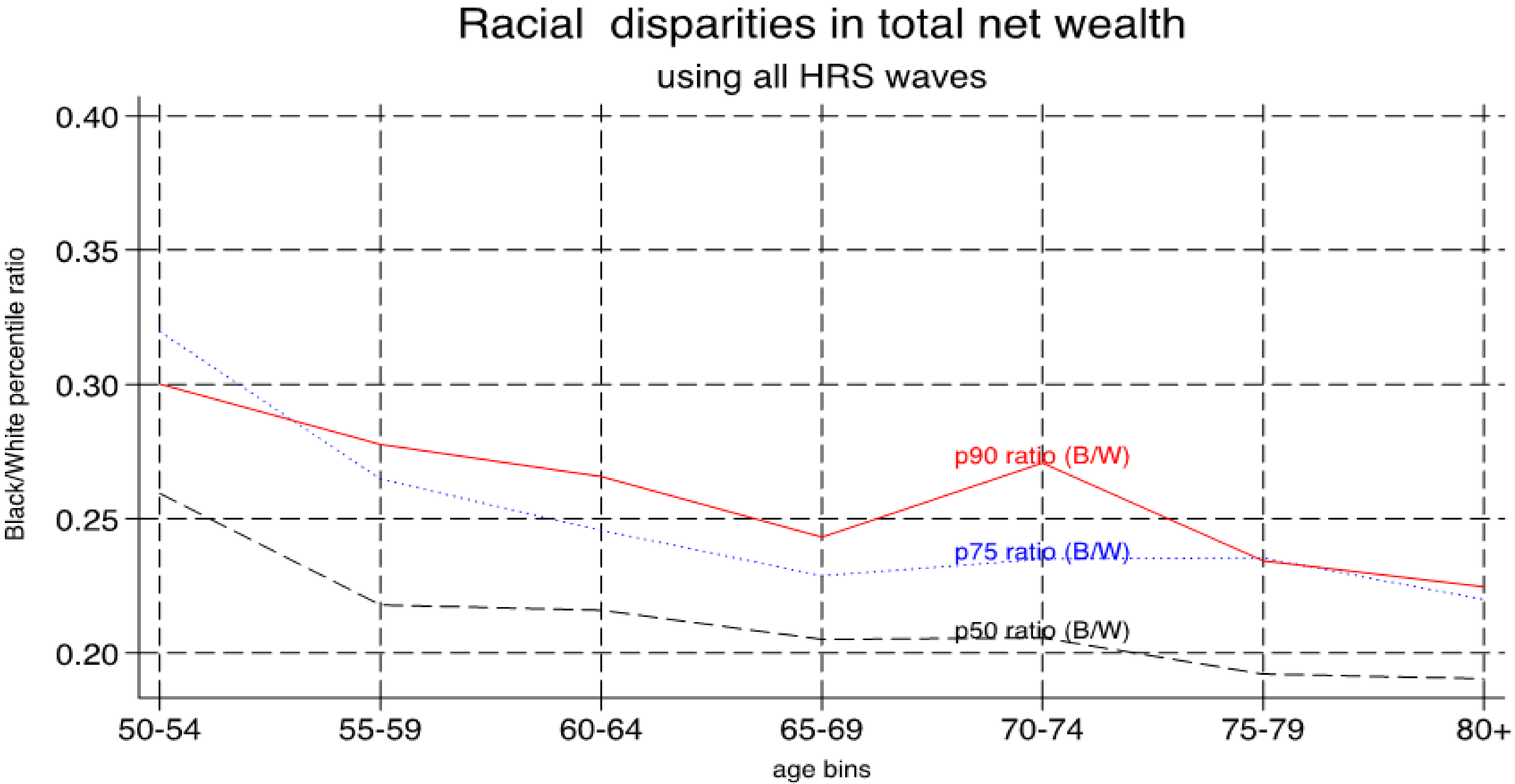
This research was supported by a grant from the U.S. Social Security Administration (SSA) as part of the Retirement and Disability Research Consortium (RDRC). The findings and conclusions are solely the those of the authors and do not represent the views of SSA, any agency of the federal government, or the University of Wisconsin-Madison's Center for Financial Security, or the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

Key Initial Results

- **Finding #1** – Widening Racial Gaps in Net Wealth with Age
- **Finding #2** -- Growing racial wealth gap over the lifecycle due to differences in rates of accumulation among the wealthiest black and white households
- **Finding #3** –Social Security Retirement does not dampen racial wealth disparities over most of the life cycle while; SSDI has declining impacts on racial wealth disparities over the life-cycle

Finding #1

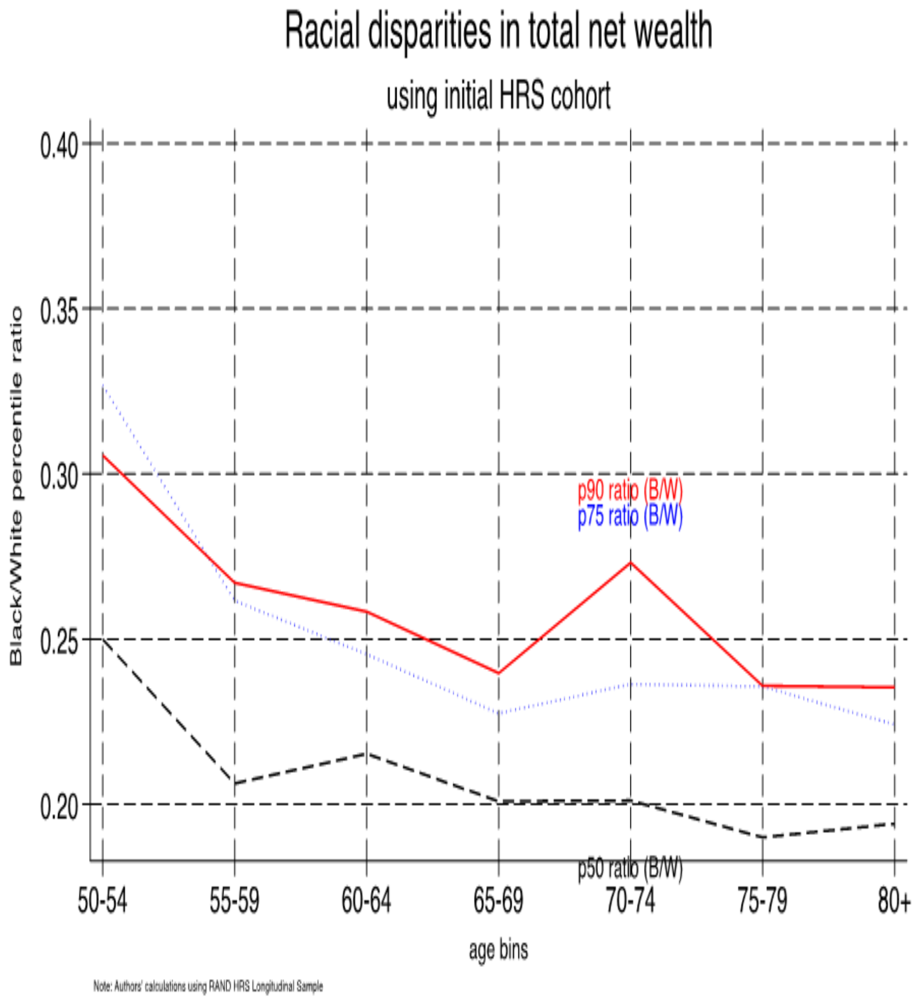
- **Data:** RAND HRS Longitudinal File
  - RAND HRS Longitudinal File 2018 (V2)
    - 14 waves of Core Interview data across sixteen survey years (1992, 1993,1994, 1995, and biennially 1996-2018)
    - 7 entry cohorts (Children of Depression/WWI; Early, Mid and late Baby Boomers)
  - Initial Analysis using combined cohorts
  - Estimating Change in Net-Wealth from Initial Wealth (t to t+n)
- **Key Finding: Widening Racial Gaps in Wealth as Households Age**



Note: Authors' calculations using RAND HRS Longitudinal Sample

Caveats

Initial Cohort



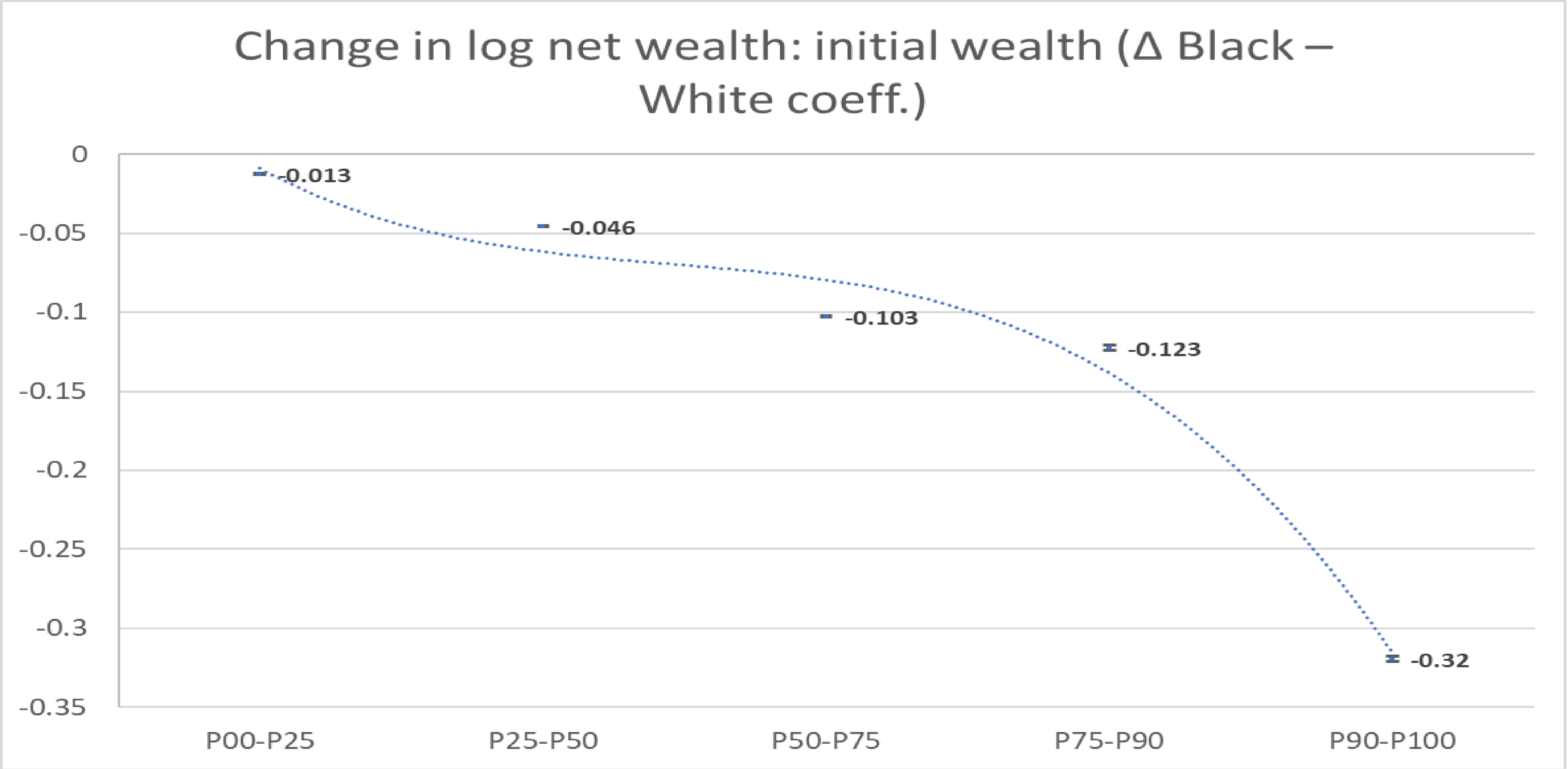
Does not distinguish among different cohorts

Does not control for holdings and type of assets/debt

Does not account for family status, health, or employment status at each age

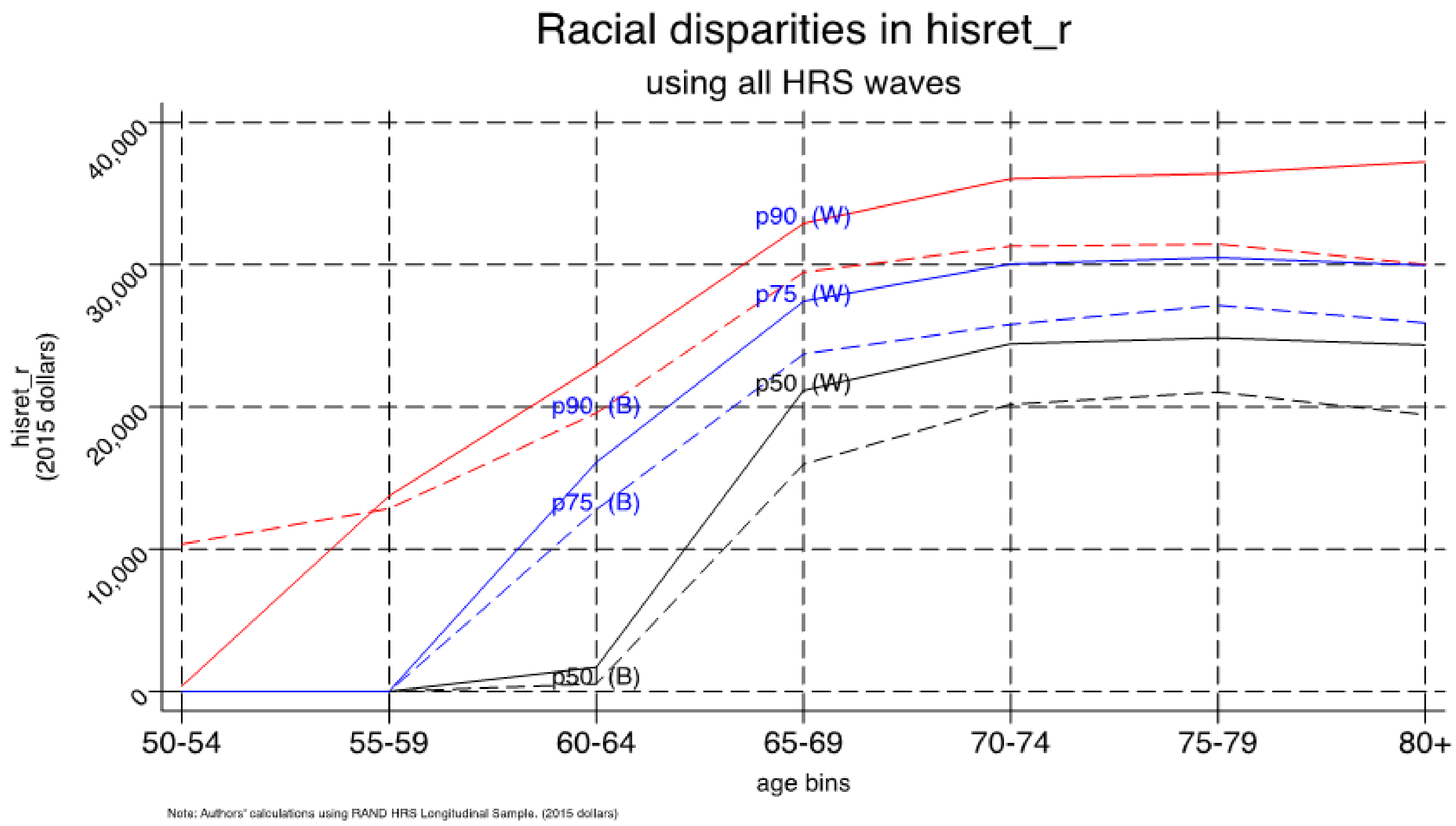
Finding #2

- Growing racial wealth gap over the lifecycle due to differences in rates of accumulation among the wealthiest black and white households
- **Estimation**
  - Change in Log Net-Wealth as function of age, race and initial wealth bins
  - Report: difference in Black – White Coefficients on wealth percentiles:
    P00-P25; P25-P50; P50-P75; P75-P90; P90-P100


Change in log net wealth: initial wealth (Δ Black – White coeff.)
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
-0.013
-0.046
-0.103
-0.123
-0.32
P00-P25
P25-P50
P50-P75
P75-P90
P90-P100

Finding #3

- Wide Racial Gaps in Social Security Income Receipts at All Ages
- Neither Social Security Disability Insurance Nor Social Security Retirement Closes these gaps

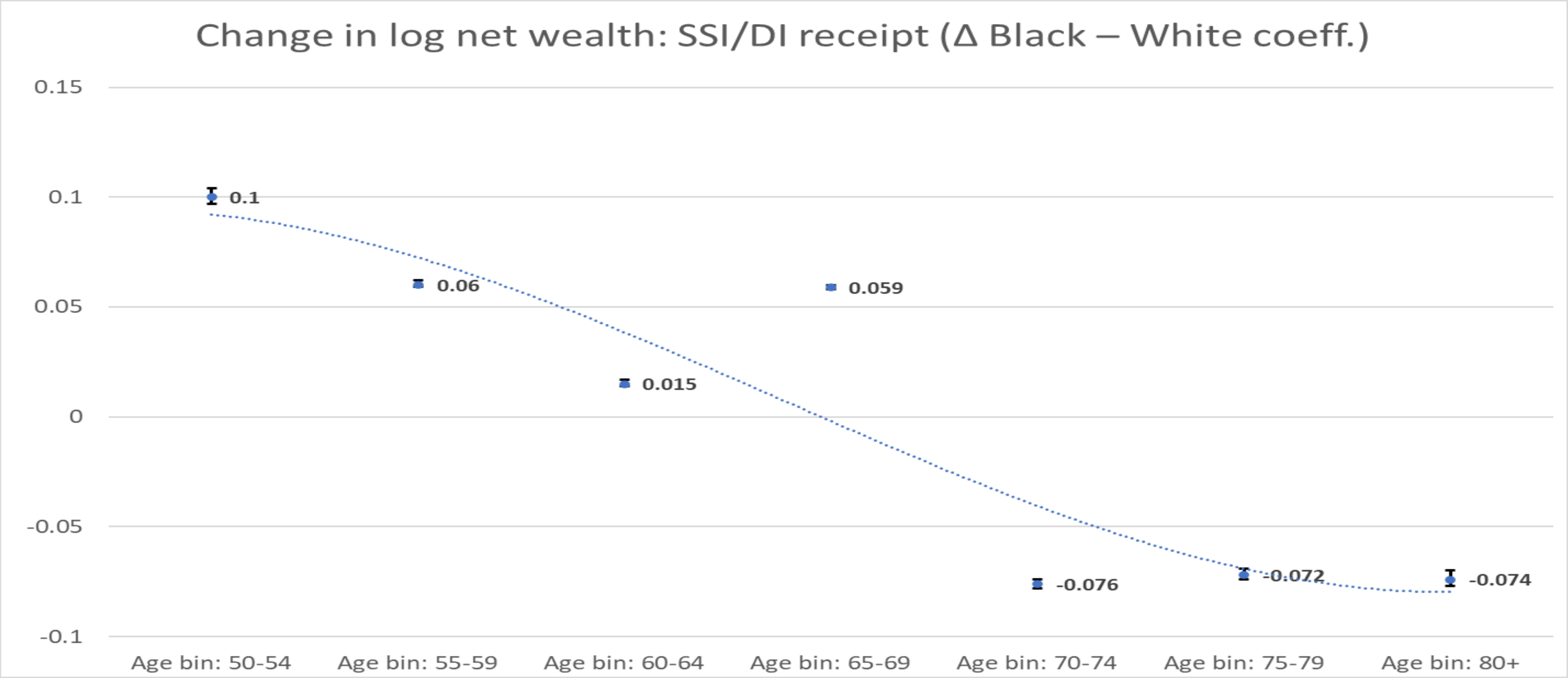


Racial Gaps in Social Security Retirement Income

Top 10% of Blacks ages 80+ receive the same as the top 25% of whites

At every age Social Security retirement income is lower for blacks and whites in the same percentile ranking

SSDI Has Declining Effects on Racial Gaps in Wealth Over the Life-Cycle



Next Steps

- Account for Changes State and Federal Taxation of Social Security
- Control for health, family structure, composition of assets/debts (including housing effects)
- Account for Cohorts (Depression era/World War II, Baby Boomers)
- Decompose disparities between rates of return on assets vs asset endowments

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THANK YOU!

Who Benefits from Retirement Saving Incentives in the U.S.? Evidence on Racial Gaps in Retirement Wealth Accumulation

Taha Choukhmane Jorge Colmenares Cormac O'Dea
Jonathan Rothbaum Lawrence Schmidt

August 2023

Disclaimer

This report is released to inform interested parties of ongoing research and to encourage discussion. Any views expressed on statistical, methodological, technical, or operational issues are those of the authors and not necessarily those of the U.S. Census Bureau. The data in this paper has been cleared by the Census Bureau's Disclosure Review Board release authorization number CBDRB-FY22-SEHSD003-001, CBDRB-FY22-SEHSD003-017, CBDRB-FY22-SEHSD003-033 and CBDRB-FY23-SEHSD003-043.

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Introduction

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- This institutional design benefits those who can and do save more for retirement
- We link newly-collected data on employer retirement plan to administrative data to study the distributional impact of these incentives

Questions and Motivation

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3. Many do not take full advantage this incentive (ave foregone match is $\approx$ 1.25%)
4. Importance of channel rising as growth of DC centers intensive margin saving choice

Literature

- <u>Wealth and Race in the US</u> Blau & Graham (1990), Barsky et al. (2002), Altonji & Doraszelski (2005), Wolff (2017), Aliprantis et al. (2019), Ganong et al. (2020), Bhutta et al. (2021), Derenoncourt et al. (2022), Avenancio-Leon & Howard (2020), Brown (2021), Francis & Weller (2021), Kermani & Wong (2021), Hou & Sanzenbacher (2021)

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- Intergenerational wealth persistence & heterogeneity in rates of return Benhabib et al. (2017), Fagereng et al. (2020), Waldkirch et al. (2004), Charles et al. (2014), Chetty et al. (2019), Fetter et al. (2022)

  Contribution: importance of interplay bw/ **parental resources** and **rates of return**

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  - Matching schedules, vesting schedules, auto-features, etc...

Form 5500 has *narrative* descriptions of:

- Eligibility
- Matching schedule
- Vesting schedule
- Auto-features

Contributions - Each year, participants may contribute from 1% to 50% of their pre-tax annual compensation, as defined by the Plan, subject to the Internal Revenue Code limitations. Eligible employees are automatically enrolled as participants at a contribution rate of 1% of their pre-tax annual compensation unless they elect otherwise. Participants age 50 and older, or who reach age 50 during the Plan year, are eligible to contribute an additional pre-tax dollar amount per year in addition to the deferral contribution. For 2011, the maximum annual amount of catch up that could be contributed was $5,500. The Company makes contributions to the Plan each payroll period, based upon a matching formula applied to employee deferrals (the Company Match). The Company Match formula is as follows: the first 3% of contributions are matched by the Plan Sponsor at the rate of 100%; the next 2% of contributions are matched at the rate of 50%; and the next 1% of contributions are matched at the rate of 25%. Participants are eligible to receive the Company Match pursuant to the terms of the Plan. Participants may also contribute amounts representing eligible rollover distributions from other qualified plans.

Participant Accounts - Individual accounts are maintained for each Plan participant. Each participant's account is credited with the participant's contribution, the Company Match, and an allocation of Plan earnings, and charged with benefit payments and allocations of Plan losses and investment expenses. Allocations are based on participant earnings or account balances. The benefit to which a participant is entitled to is the benefit that can be provided from the participant's vested account balance.

Vesting - All participants are 100% vested in the Plan at all times.

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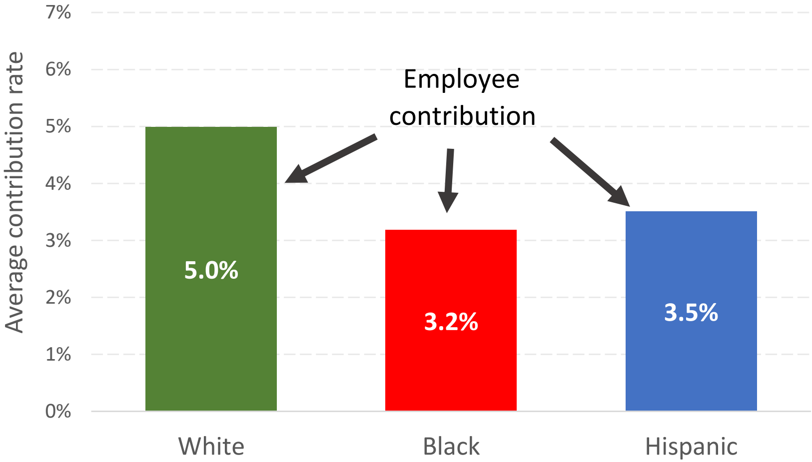
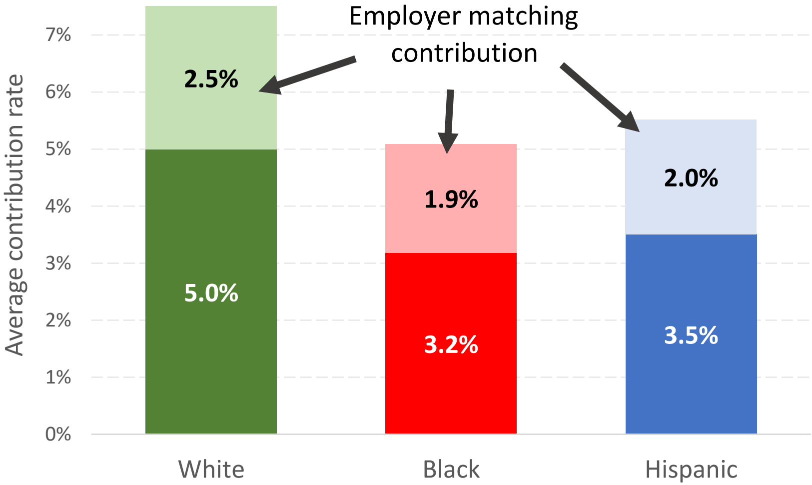
5. Parental resources play a role

1. Gaps in retirement saving by race are large



2. Employer matching contributions amplify the effect of gaps



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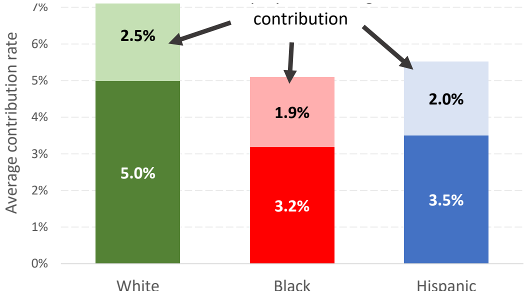

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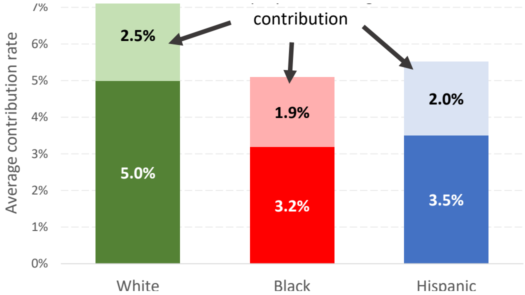

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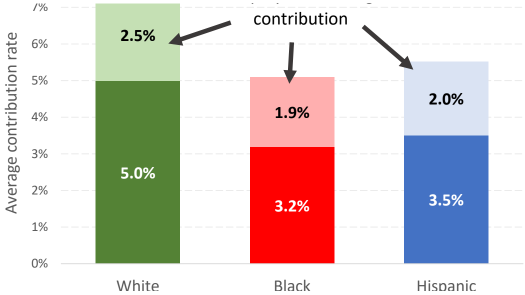

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More

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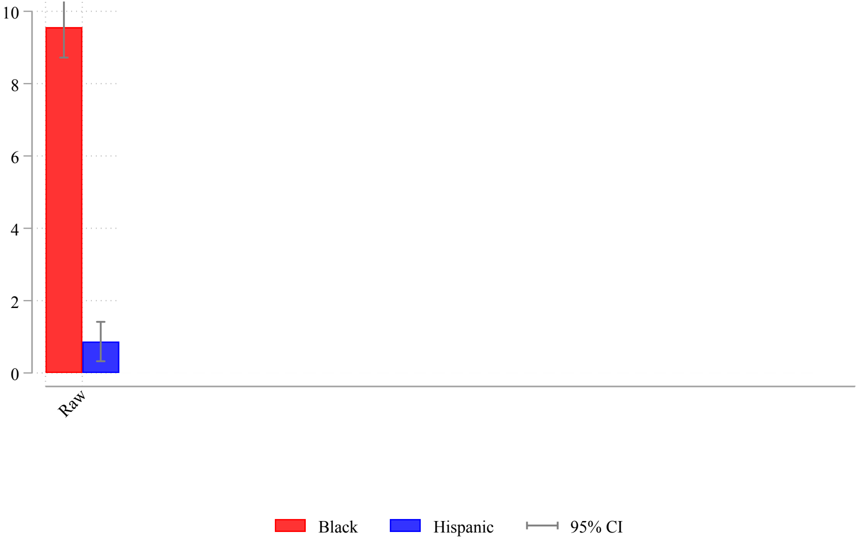

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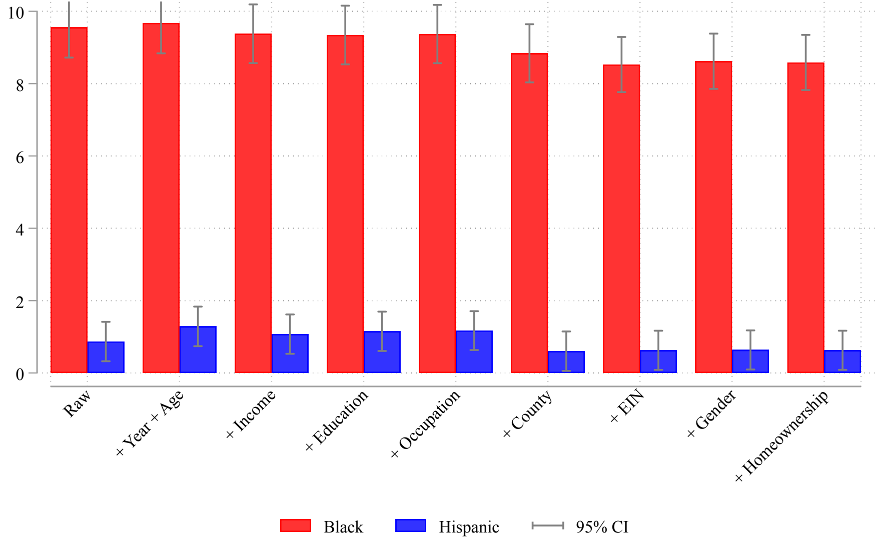

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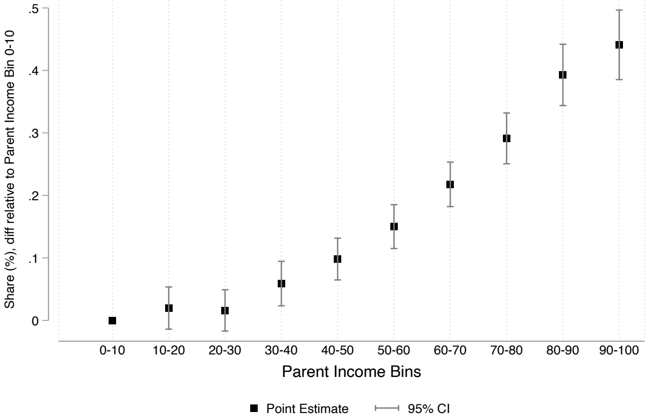

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Regressive subsidies for private saving...

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Other dimensions matter **(conditional on income)** for take-up and are not undone by SS

Magnitudes and Distributional Features

Estimates for employee + employer contrib. in saturated model (inc. income, race, EIN, individual/family attributes)

Traditional focus:

Moving from 2nd to 9th decile of labor income = +1.1% higher total contrib. ▸ income

Controlling for income and other attributes:

- **Race:** Black (Hispanic) workers contribute 1.1% (0.4%) less than White workers
- **Parental Income:** parents previously in top decile of income = +0.44% employee contrib ▸ parent
- **Education:** College degree = +1.4% higher contrib. ▸ education
- **Spousal Support:** spouse in top decile of labor income = +2.9% ▸ spouse
- **Family Structure:** Two-person households save up to 0.37%, and couples (singles) without kids save up to 1.2% (1.1%) more.

Evaluating the impact of institutional support for savers

- We evaluate overall distributional impact of institutional support for those who save most:
  1. Employer matches (which link remuneration to private saving)
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- To measure effect of counterfactual policies on wealth we need a simulation model with:
    - Income
    - Employee retirement saving
    - Employer matches
    - Social Security
    - Wealth

- Details to come in the paper

Conclusion

- Current system relies on **incentives** for saving and **disincentives** for early withdrawals
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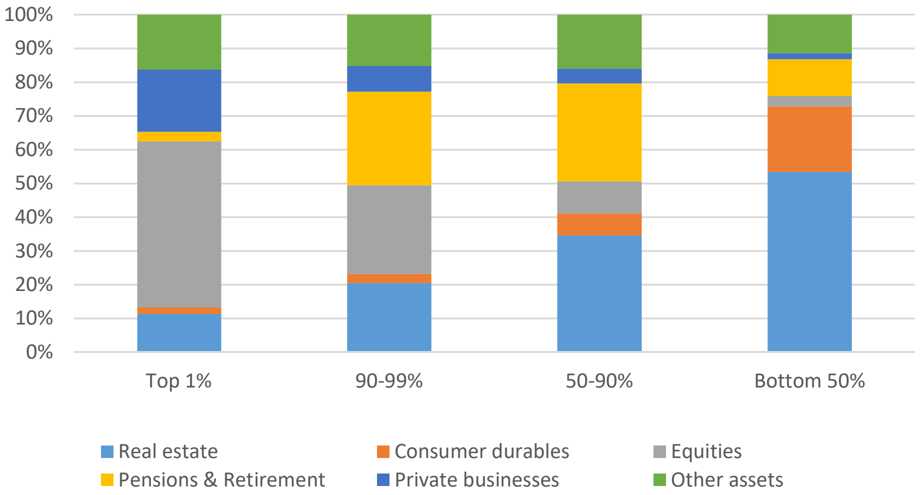
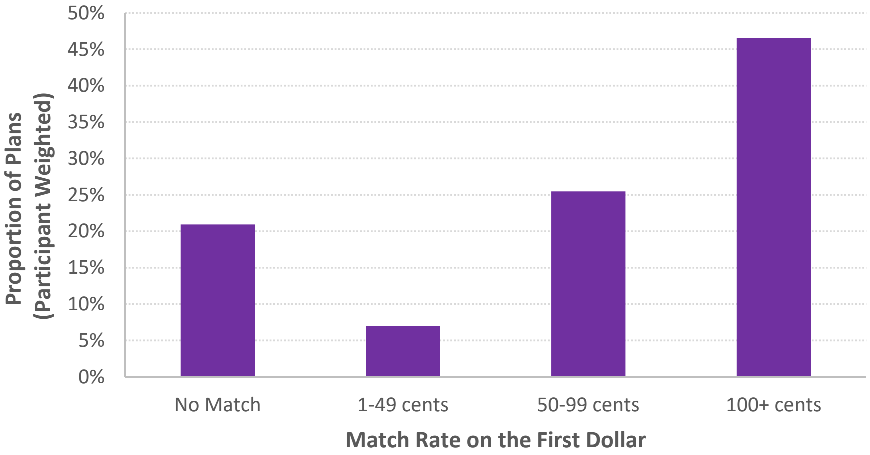
  - **system amplifies racial wealth gaps** and intergenerational persistence
- Broader take-aways for the retirement system:
  - Distributional analysis should look beyond income
  - Likely to be benefits from increasing liquidity (changing loan & withdrawal penalty policies)

Retirement accounts are a large share of household wealth



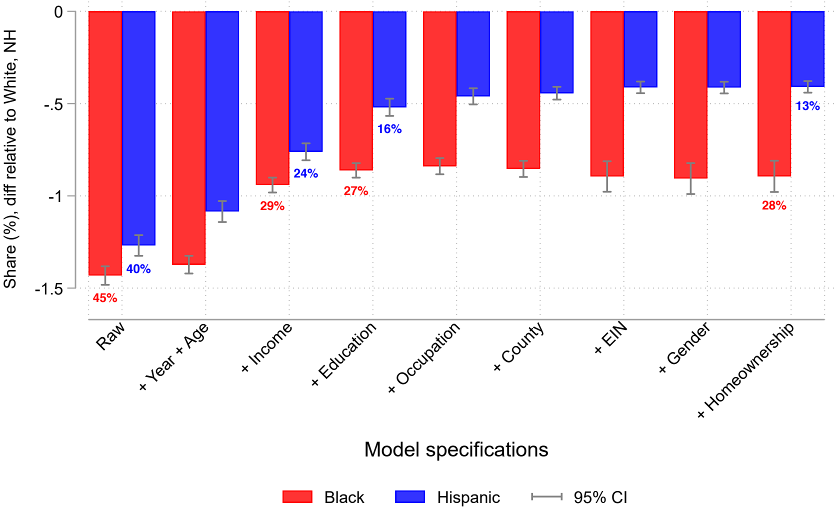
Source: Federal Reserve Board (2022), Distributional Accounts Back

Distribution of match rates on first dollar of saving



Back

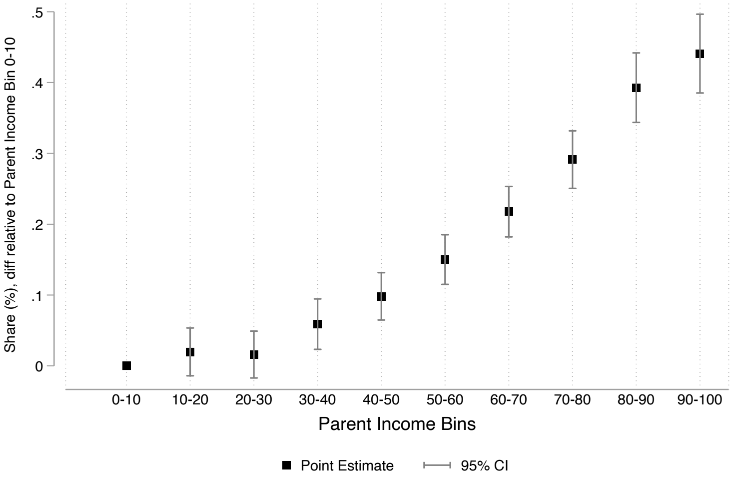
3. Gaps remain after controlling for individual characteristics



Dependent Variable: Contribution rate ≡ DC employee contribution / Total W2 income

Do the (kids of the rich) save more?

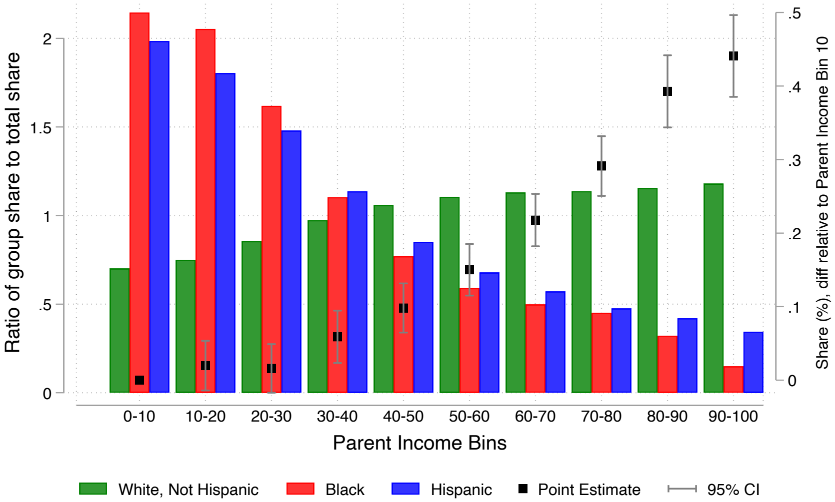
Holding own-characteristics constant, those with richer parents contribute more



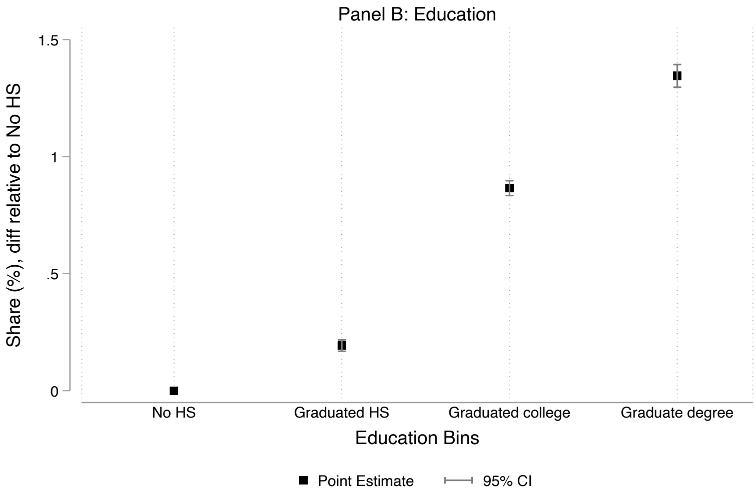
Back

The role of parental income

Conditional on own-income, White Americans have richer parents than Black or Hispanic Americans



Education



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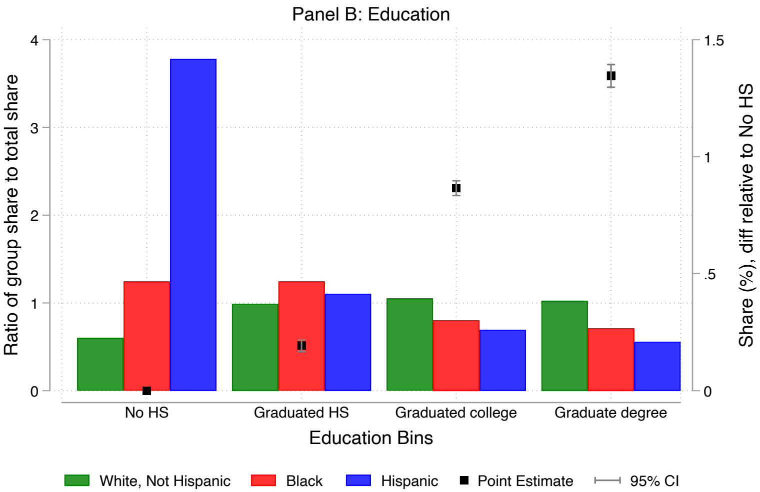
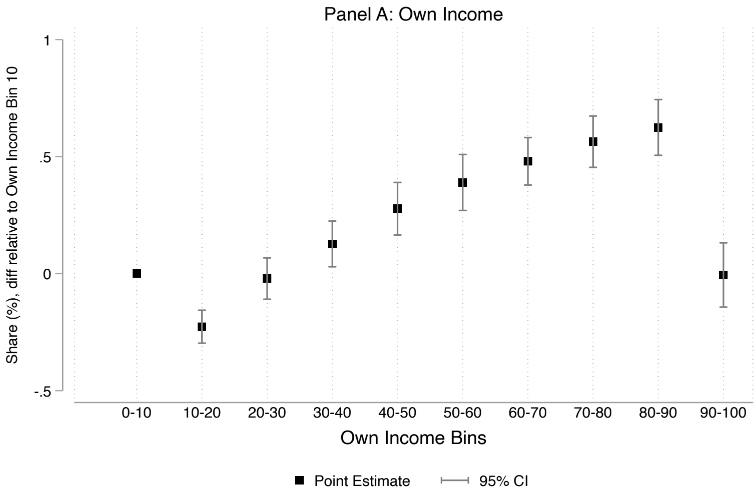


Panel B: Education
Ratio of group share to total share
Share (%), diff relative to No HS
4
3
2
1
0
1.5
1
.5
0
No HS
Graduated HS
Graduated college
Graduate degree
Education Bins
White, Not Hispanic
Black
Hispanic
Point Estimate
95% CI

Own Income



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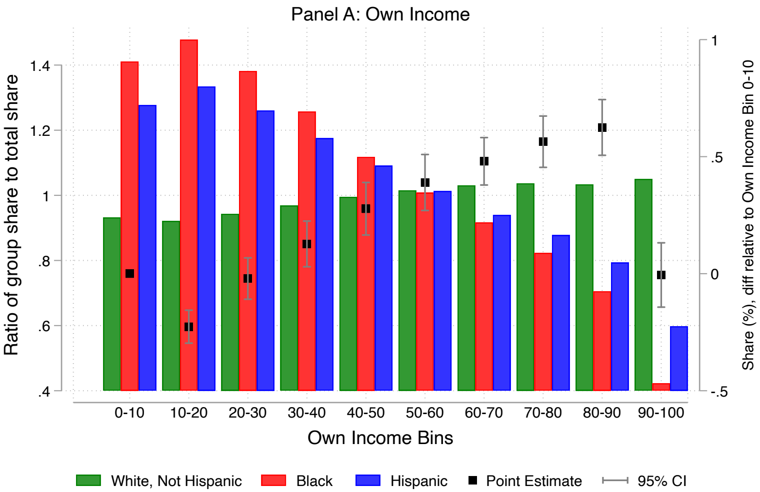
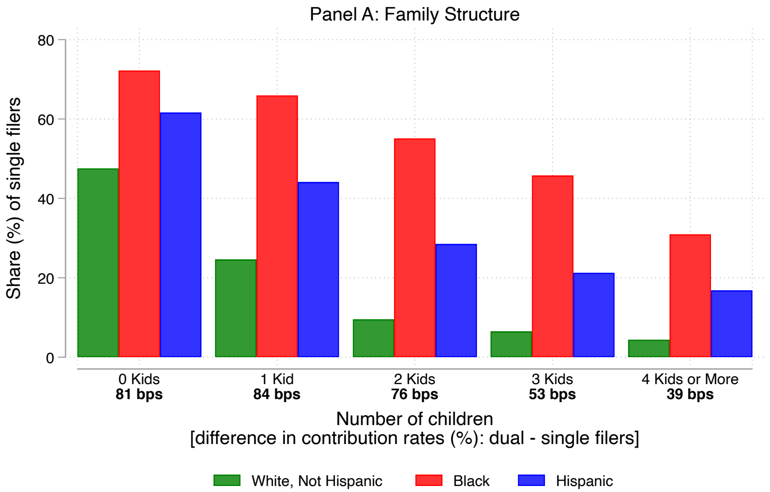
Own Income


Panel A: Own Income
Ratio of group share to total share
1.4
1.2
1
.8
.6
.4
Share (%), diff relative to Own Income Bin 0-10
1
.5
0
-.5
0-10
10-20
20-30
30-40
40-50
50-60
60-70
70-80
80-90
90-100
Own Income Bins
White, Not Hispanic
Black
Hispanic
Point Estimate
95% CI

Family Structure



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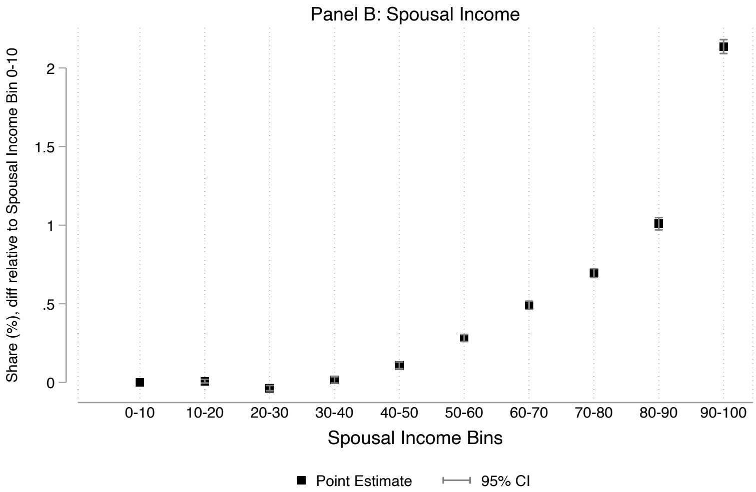
Spousal Income



Disparities by Race and Gender in SS(D)I Applications and Awards

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Acknowledgement

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Overview

- Objective: to examine disparities by race and gender in SSDI and SSI applications and awards
- Data and analysis:
  - Health and Retirement Study (HRS), and a subset of HRS linked with SSA
  - Traditional methods (e.g., regression) compared with machine learning (ML)
- Main findings:

	SSDI application	SSDI receipt	SSI application	SSI receipt
White vs. Black	Null	Null	Null	Null
Male vs. Female	**Lower for female (for both the HRS and SSA data)**	Lower for female (only for the HRS linked with SSA)	Null	Null

SSDI and SSI

- The Social Security Administration (SSA) administers the two largest federal programs providing cash assistance to people with disabilities, the Disability Insurance (DI) program, and the Supplemental Security Income (SSI) program. SSI also provides income assistance to the aged who have income and assets below a certain level.
- According to the Monthly Statistical Snapshot, February 2023 (ssa.gov) 7.5 and 8.7 million Americans received SSI and SSDI in February 2023, respectively.
- SSDI and SSI have significant impact on beneficiaries' lives, including labor supply, earnings and income, and health (e.g., Autor et al. 2016, Deshpande, 2016; Favreault, 2013)

Disparity in SS(D)I Application and Awards

- The application, appeal, and award process is much studied (e.g., Benitez-Silva et al. 1999; Kreider and Riphahn, 2000; GAO, 2023)
- It is important to study disparity in the application and award of SS(D)I to ensure fairness, impartiality, and public trust in these programs. According to Godtland et al. (2007):

> "For the public to perceive that SSA's disability programs are run with the highest degree of integrity, it is of the utmost importance that the agency's decisions to award cash benefits to people with disabilities are accurate and made in a fair and impartial manner, without regard to race, sex, or other factors not related to a person's impairment."

Literature Review: Racial and Gender Disparity

- The literature on disability benefit programs, specifically SSDI and SSI, has identified racial and gender disparities in the application and award rates. Several studies have examined the differential treatment and outcomes experienced by different racial and gender groups within the disability determination process.
  - Racial disparity: U.S. GAO (1992); Benitez-Silva et al. (1999); Hu et al. (2001); Kreider and Riphahn (2000); Godtland et al. (2007)
  - Gender disparity: Kreider and Riphahn (2000); Baldwin (1997)
- These studies collectively
  - Highlight the existence of racial and gender disparities within the disability determination process
    - with African Americans and women experiencing lower award rates and higher denial rates, particularly at certain stages
  - However, the literature review also suggests variations in findings depending on factors such as age, attorney representation, and the specific stage of the determination process

Limitations of Existing Literature

- Disparity is evaluated as an average difference between two groups (measured using an indicator for each group, e.g., d = 1 for Black and 0 for White), like an average "treatment effect".
- Existing methods rely on a regression model:
  - Some researchers estimate the coefficient on d, while controlling for as many $\mathbf{x}$'s (e.g., age, education, income, health) as possible. Doing so essentially assumes the disparity is constant (homogeneous) for all individuals, which may not be true.
    - For example, if disparity is higher (or lower) for people with lower (or higher) education, then there is an interaction effect between d and education, meaning that disparity is not homogeneous, but heterogeneous, across different levels of education. To take this heterogeneity into account, researchers often conduct subsample analyses along various dimensions (e.g., education and income) and report many subsample treatment effect estimates. Although doing so provides many insights for the treatment effect evaluation, all these subsample analyses do not directly provide an overall assessment of the treatment effect (i.e., a single number for the whole population) that can be interpreted as a "weighted average" of those subsample treatment effect estimates.
  - Some researchers control for as many "$d \times \boldsymbol{x}$" as possible, and then estimate the coefficients on d and those many "$d \times \boldsymbol{x}$", and then compute the "marginal effect" of d. Doing so allows the "treatment effect" to vary by $\boldsymbol{x}$, and then the "average treatment effect (ATE)" would accommodate the treatment effect heterogeneity due to observables. Doing so also implicitly computes a "weighted average" of those subsample treatment effect estimates (discussed above). But:
    - Specifying those interaction terms can be a subjective decision when there is little guidance in theory;
    - Estimating this heterogeneous ATE can be infeasible, because the overlap assumption can be violated when there are many $\boldsymbol{x}$'s used as control variables. This violation is often made explicit in the implementation of propensity-score-based estimators. But, when using the OLS, we may not receive an error message telling us that the overlap assumption is violated.

Our Contributions

- We use a new method to estimate an “average treatment effect (ATE)” between two groups, which we interpret as the disparity between these two groups.
- This new method allows the ATE to vary by individuals; it also captures the interactions between *d* and ***x***’s in a flexible, data-driven way.
- To satisfy the overlap assumption, this new method utilizes machine learning (ML) techniques to conduct “dimension reduction” (i.e., selecting only relevant variables for predicting the dependent variable based on the data used for analysis).
  - Our study uses a large set of potential predictor variables—**830** variables, coming from individual-level characteristics (linear term and quadratic term), state dummy variables, state dummy variables interacted with individual-level characteristics.
- This new method was proposed by Chernozhukov et al. (2018), called *double/debiased ML estimator*. To the best of our knowledge, we are the first to apply this estimator to the setting of analyzing disparities.
  - In particular, this estimator incorporates ML techinques in a way that allows for statistical inference (i.e., conducting hypothesis tests), whereas many commonly seen and used ML techniques are only suitable for generating predicted values for a dependent variable and not suitable for analyses that involve hypothesis tests.

Clarifications

- In this study, we focus on the *comparison* between estimates obtained by a traditional and still widely used method—the ordinary least squares (OLS), and the double/debiased ML estimator. Essentially, we examine whether our conclusion about the presence of an overall disparity (averaged across different segments of a population) will change if we conduct "case-by-case" (i.e., allowing d to interact with $\boldsymbol{x}$) analyses in a data-driven way.
- Because of this focus, we use the same sample for both estimations. We do not conduct sample-selection-bias corrections. That is, the sample being used for both estimations may contain sample-selection-bias, but we ignore it. We do not focus on obtaining an unbiased or consistent ATE estimate. Instead, we find that the disparity suggested by the OLS estimates might not be present, once we use alternative methods such as the double/debiased ML estimator.
- Our study is about detecting the presence of a disparity, using the double/debiased ML estimator. This estimator does not allow us to pinpoint the underlying mechanism generating that disparity.
- To tighten the focus of our study, we consider White vs. Black and Male vs. Female comparisons.
  - HRS data: "1: white; 2: black; 3: others"; White: 77%; Black: 17%; Others: 6%
  - HRS data: "1: yes Hispanic; 0: no"; Hispanic: 10%
  - HRS data: "1: male; 2: female"; answers are self-reports by the HRS respondents at the time of the interview, not the recorded information in birth certificates. Thus, we interpret "Male or Female" as gender, instead of sex assigned at birth.

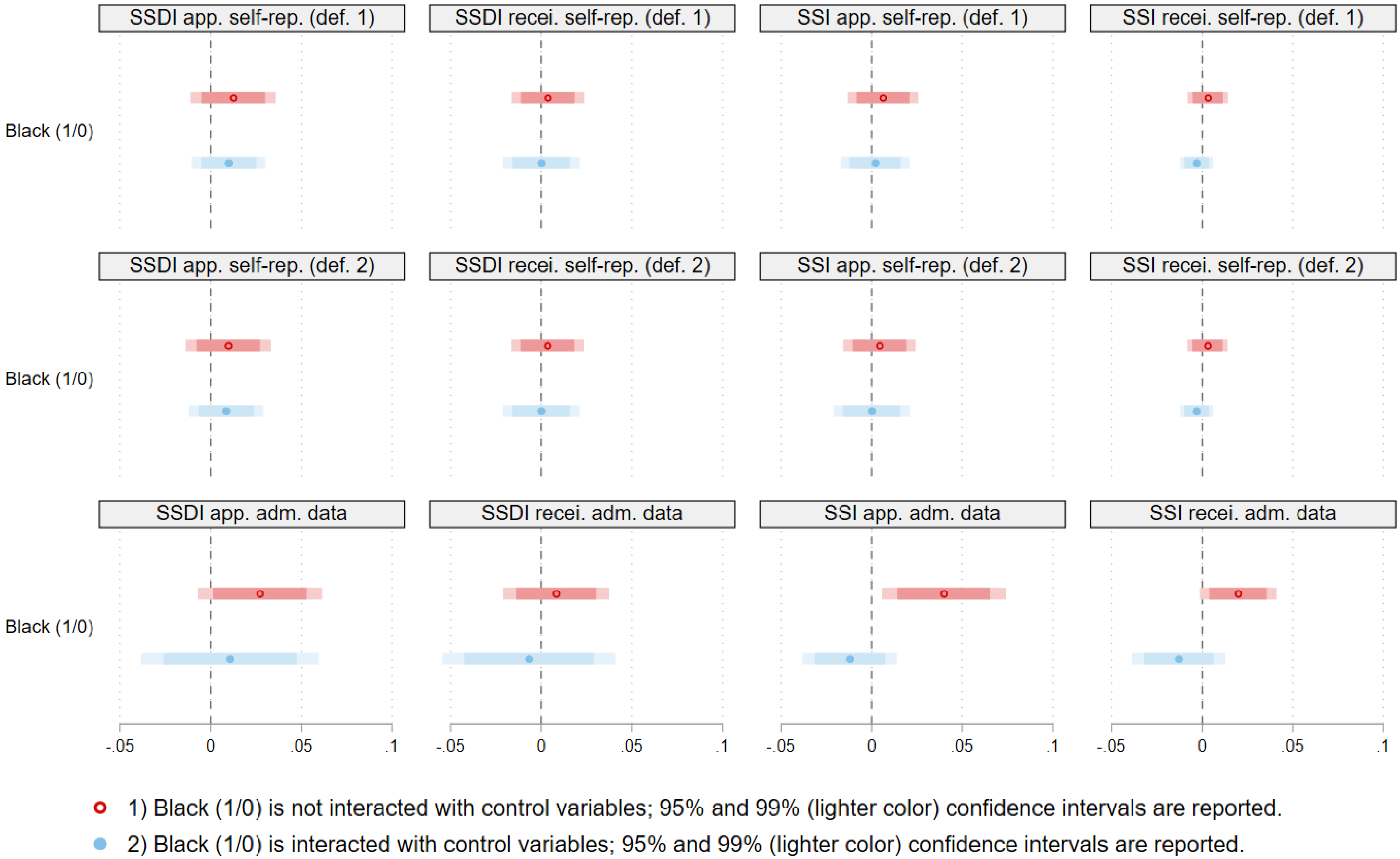
Data

- Health and Retirement Study (HRS) linked to SSA's data on SS(D)I applications and awards
- HRS: a nationally representative sample for respondents over the age of 50
- HRS has self-reported SS(D)I application and receipts, while HRS-SSA linked data contain information on SS(D)I applications and receipts for those HRS respondents who *consented to be linked to SSA* and applied for disability benefits under Title II (SSDI) and Title XVI (SSI).
  - Not all individuals in the HRS who have applied for or have been awarded SS(D)I benefits will be identified by the HRS-SSA linked data. We conduct analyses using the HRS data and the HRS-SSA linked data separately.
- We focus on whether ever applying for/receiving SS(D)I during 2006–2018. This is the period in which HRS data linked with SSA records are available.
  - We tighten the focus of our study to investigating the disparities along racial and gender dimensions rather than the dynamics of SS(D)I applications and awards. As a result of this tightened focus, we aggregate the data across multiple waves of the HRS survey data, resulting in a cross-sectional dataset.
- Construction of the measures of application for and receipt of SSI/SSDI follows the Appendix A of the paper by Hyde and Harrati (2021).

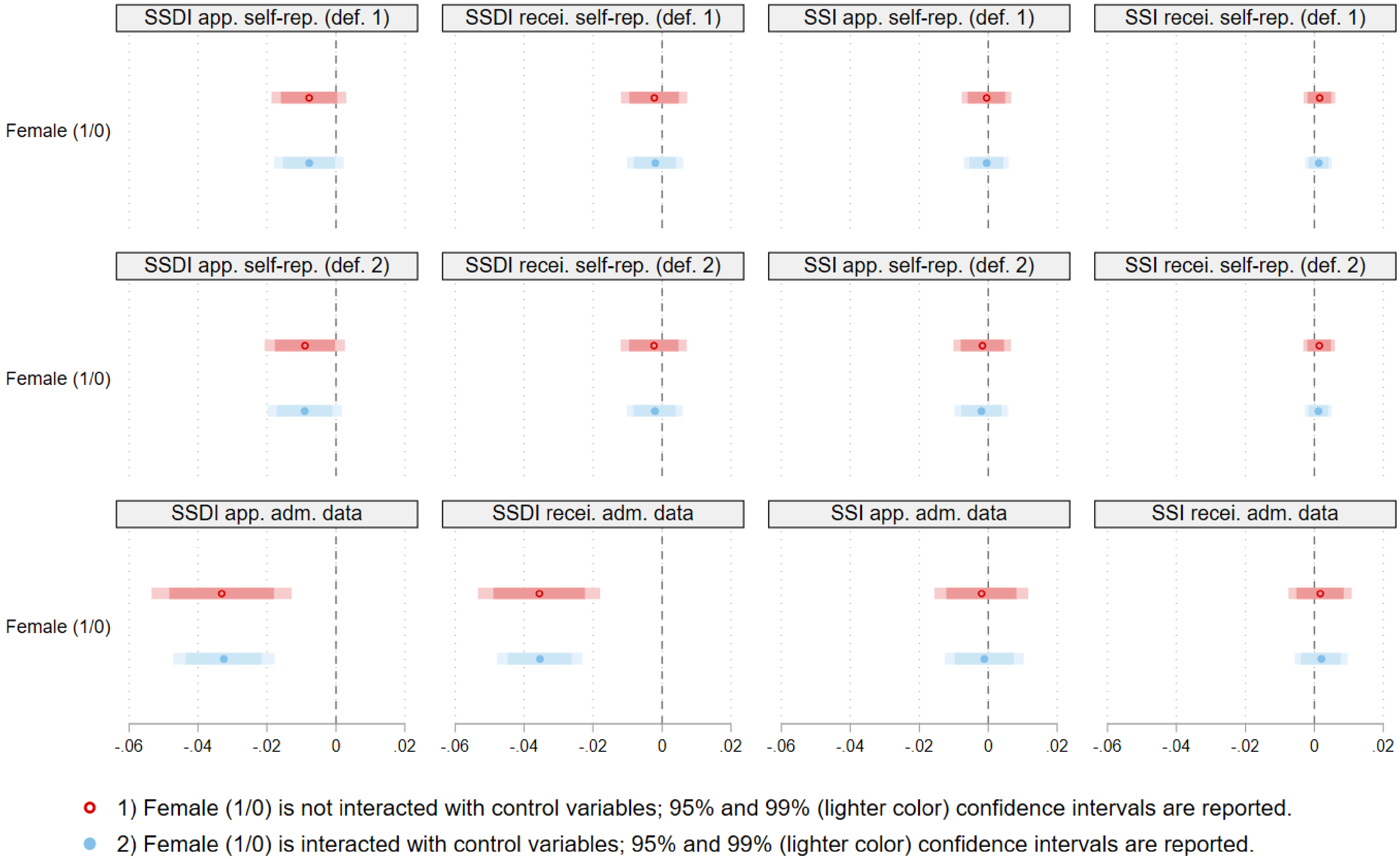
Double/Debiased ML Estimator: Notes

- The double/debiased ML estimator includes three techniques: (1) the least absolute shrinkage and selection operator (LASSO); (2) cross-fitting; (3) resampling.
- We use LASSO to conduct dimension reduction.
- Cross-fitting is used for allowing more predictor variables, relative to the sample size, to be selected.
    - In our study we use a 10-fold crossing-fitting, since using 10 folds is a standard practice for conducting cross-fitting.
- One drawback of cross-fitting is that it introduces randomness into the ATE estimate, since how the original sample is divided into multiple folds is random. One solution is combining cross-fitting with resampling, which is repeating cross-fitting multiple times using resamples of the original sample, and then averaging the resulting estimates.
    - In our study we use three resamples, meaning that we conduct the 10-fold cross-fitting three times.
- In one of our robustness checks, we require certain variables, such as demographic variables, to be always included as predictor variables instead of being determined by the LASSO technique, in order to assess whether our ATE estimates are sensitive to the data-driven approach used by the LASSO.

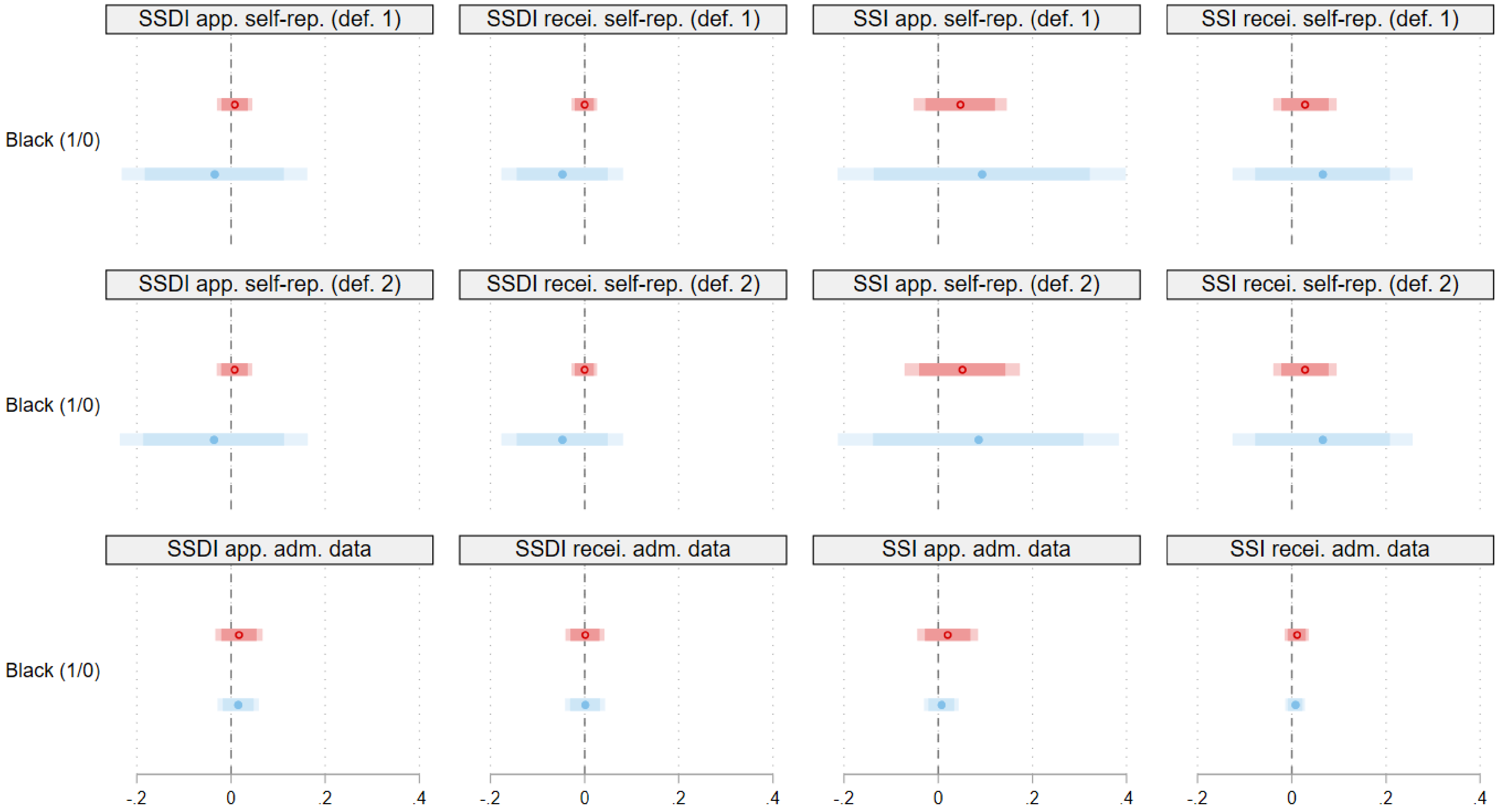
Analysis of the Ordinary Least Squares Estimates of Racial Disparity



Analysis of the Ordinary Least Squares Estimates of Gender Disparity

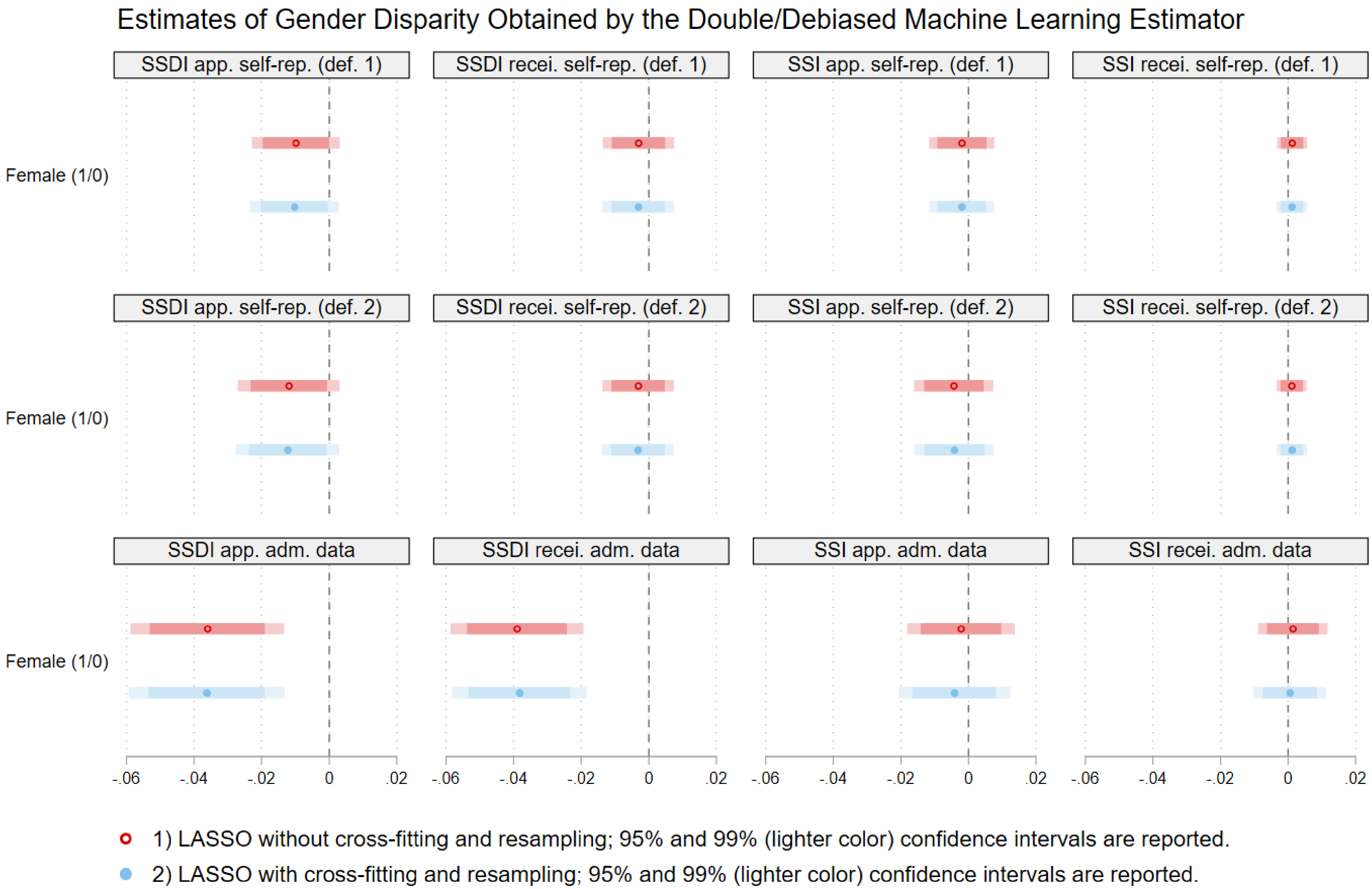


Estimates of Racial Disparity Obtained by the Double/Debiased Machine Learning Estimator



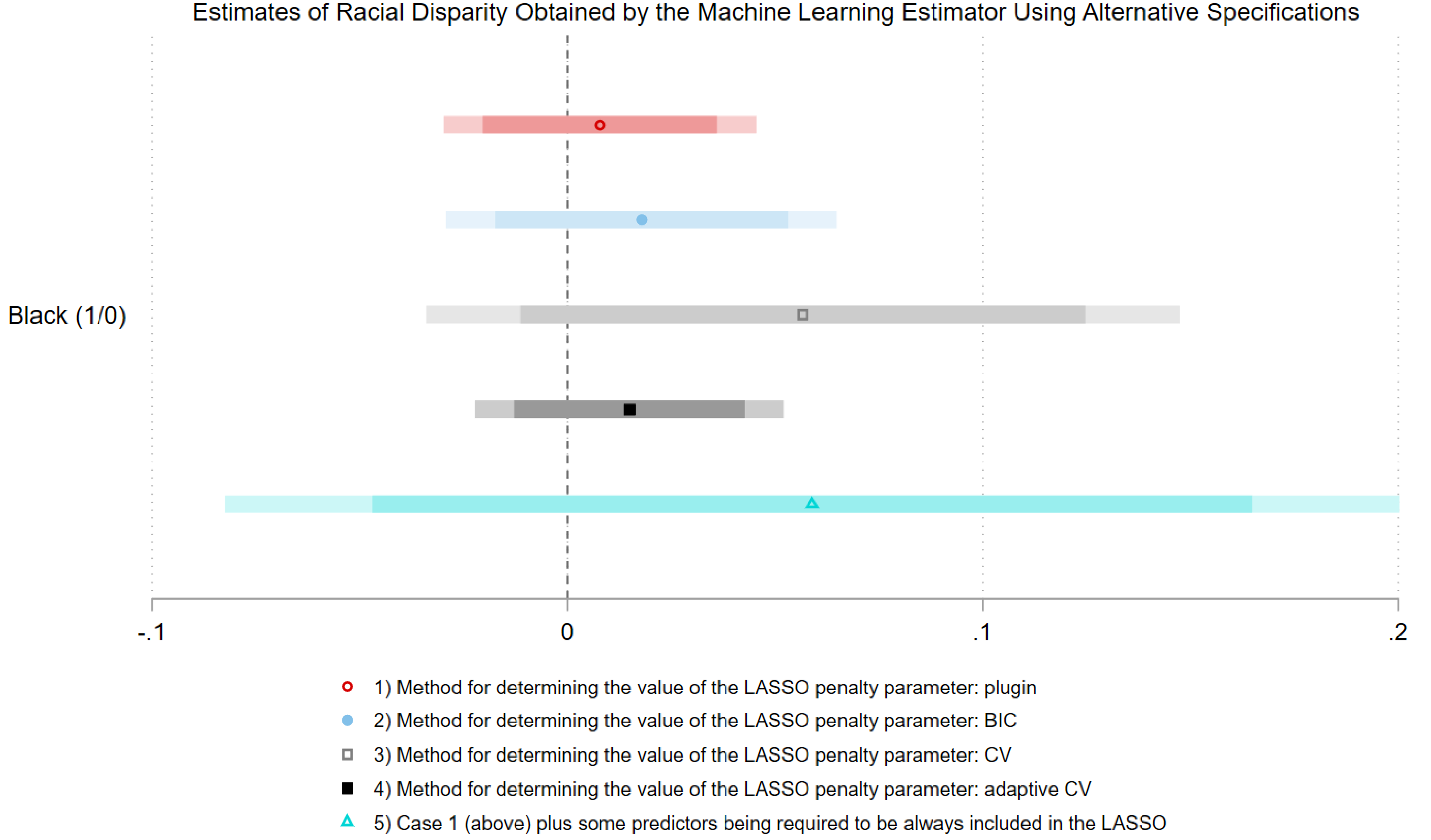
1) LASSO without cross-fitting and resampling; 95% and 99% (lighter color) confidence intervals are reported.

2) LASSO with cross-fitting and resampling; 95% and 99% (lighter color) confidence intervals are reported.



Estimates of Gender Disparity Obtained by the Double/Debiased Machine Learning Estimator
SSDI app. self-rep. (def. 1)
SSDI recei. self-rep. (def. 1)
SSI app. self-rep. (def. 1)
SSI recei. self-rep. (def. 1)
SSDI app. self-rep. (def. 2)
SSDI recei. self-rep. (def. 2)
SSI app. self-rep. (def. 2)
SSI recei. self-rep. (def. 2)
SSDI app. adm. data
SSDI recei. adm. data
SSI app. adm. data
SSI recei. adm. data
Female (1/0)
Female (1/0)
Female (1/0)
-.06
-.04
-.02
0
.02
1) LASSO without cross-fitting and resampling; 95% and 99% (lighter color) confidence intervals are reported.
2) LASSO with cross-fitting and resampling; 95% and 99% (lighter color) confidence intervals are reported.

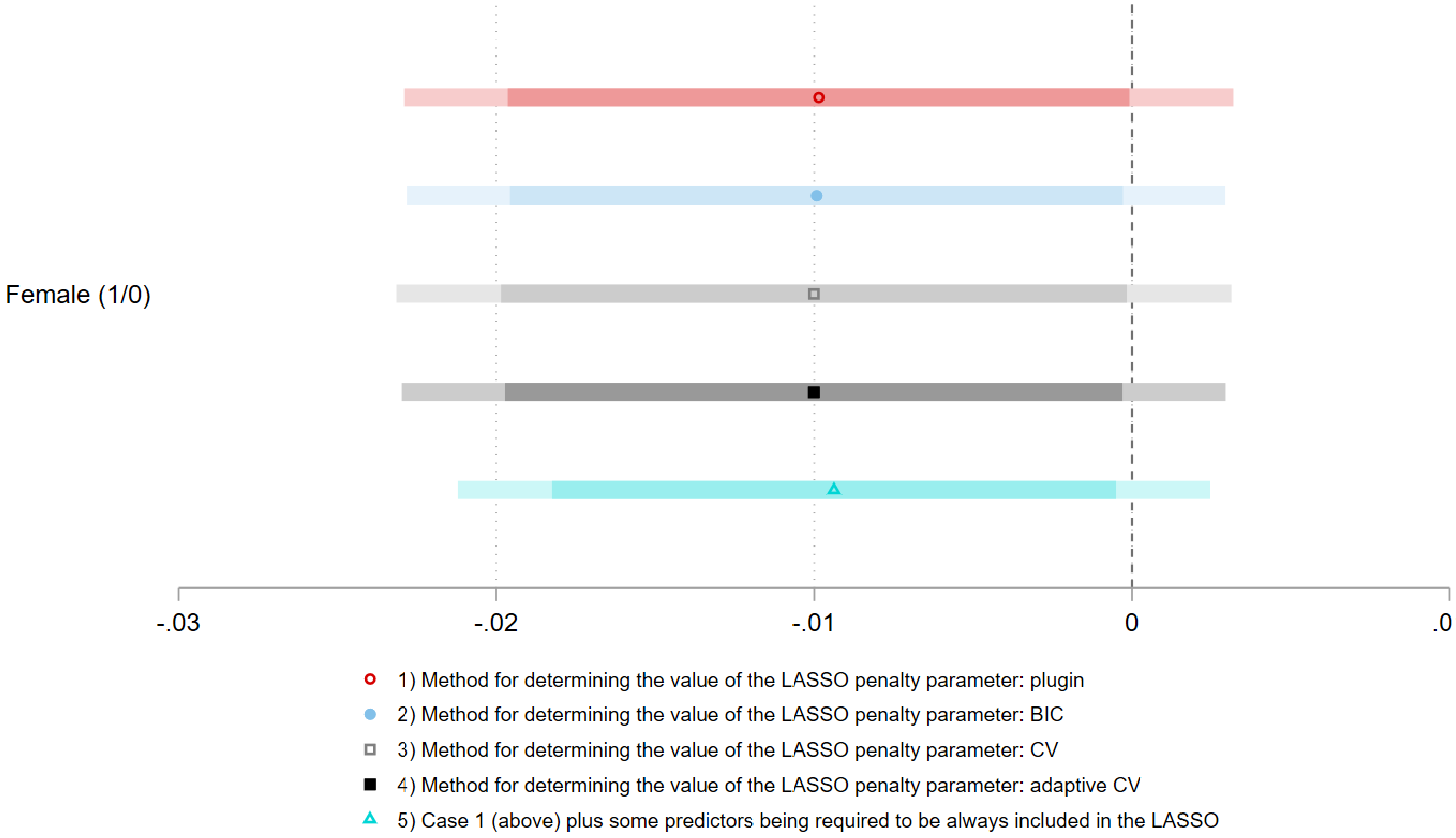
Dependent variable: SSDI application, self-reported (definition 1)



Point estimates (weighted means) and the confidence intervals at the 95% level and the 99% level (in lighter color) are reported in the figure (standard errors clustered by state).

Dependent variable: SSDI application, self-reported (definition 1)

Estimates of Gender Disparity Obtained by the Machine Learning Estimator Using Alternative Specifications



Point estimates (weighted means) and the confidence intervals at the 95% level and the 99% level (in lighter color) are reported in the figure (standard errors clustered by state).

Conclusion

1. No findings on racial disparity in SSI or SSDI applications or receipts.
2. Females are less likely to apply for SSDI compared to males. No findings on gender disparity among other dimensions.
3. Our method allows us to detect the presence of a disparity, and in doing so we take into account possible interactions between race/gender and observable characteristics in a flexible (i.e., data driven) way.
4. However, our method does not allow us to identify the underlying mechanism generating that disparity. Therefore, we must limit the conclusion of our study to whether a disparity is detected or not, as opposed to discussing policy implications about how to reduce disparities.

Policy Implications

1. Our findings provide insights into the effectiveness of the SS(D)I program in reaching individuals with disabilities across different racial and gender groups. These findings can be useful to evaluate the programs' performance and identify potential gaps or biases in the program and implement targeted policy interventions to address these disparities
   - Policies could focus on providing additional resources and support to marginalized groups, improving outreach efforts to ensure equal access to information about the disability benefits program, and reducing barriers that disproportionately affect certain racial and gender groups
2. Our research findings can be useful to implement measures aimed at mitigating bias and discrimination in the SS(D)I application and award process
   - This may involve reviewing and revising the evaluation criteria, ensuring that decision-making processes are fair and unbiased, and providing training and guidance to program administrators to address implicit biases that may impact application outcomes
3. Our findings emphasize the importance of comprehensive data collection and monitoring systems to track and address potential disparities in SS(D)I applications and awards
   - This may involve incorporating data on race and gender in program evaluation processes and regularly assessing the programs' performance in reaching diverse populations. Robust data collection enables researchers and policymakers to identify emerging trends, evaluate the impact of policy changes, and ensure accountability in addressing disparities

Thank you!

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