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

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Abstract

U.S. employers and the federal government devote more than 1.5% of GDP annually towards promoting Defined Contribution retirement saving. We study the distributional and lifetime impact of these savings incentives across racial groups using a new employer-employee linked data set covering millions of Americans. The average contribution rate of Black and Hispanic workers is roughly 40% lower than that of White workers. The rich and the children of the rich save more; racial differences in own and parental incomes account for a large share of the racial contribution gaps. Tax and employer matching subsidies further amplify these saving differences by channeling more resources to those who save more. We estimate that breaking the link between contribution choices and saving subsidies, through revenue-neutral reforms, would significantly reduce racial gaps and intergenerational persistence in wealth.

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1 Introduction

Every year, the equivalent of 1.5% of U.S. GDP is devoted to encouraging contributions to retirement savings plans such as 401(k) and 403(b) accounts.[1] Around 100 million Americans have access to such plans through their employers, and these accounts offer an attractive vehicle for long-term saving. Contributions are taxed favorably, and over 80% of employers further subsidize savers by matching their employees' contributions (Arnoud et al. (2021)). At an average match of approximately 50 cents per dollar contributed, saving in a tax-favored employer-sponsored account is one of the best, if not *the best*, financial investment opportunities available to build wealth. This institutional design, therefore, rewards those who can, and do, save more for retirement. Employees who do not contribute receive neither tax benefits nor employer-matching contributions.

In this paper, we use newly collected data on employer-sponsored retirement plan characteristics combined with administrative data on the contribution and withdrawal behavior of millions of American employees to study the distributional impacts of the design of retirement saving institutions, with a particular focus on impacts by race. The data show large gaps in retirement saving across the three largest racial and ethnic groups in the U.S.: non-Hispanic White, non-Hispanic Black, and Hispanic employees.[2] Black and Hispanic workers with access to a 401(k) or a 403(b) plan and a modest degree of labor market attachment (at least $8,000 in annual earnings) contribute approximately 40% less (or, respectively, 1.8 pp and 1.6 pp of salary less) than White workers (Figure 1A). Employer matching amplifies these contribution gaps by an additional 0.7 and 0.6 pp, respectively, of salary. We find that employer matching and tax benefits are more unequally distributed than wages, as illustrated in Figure 1B. While the median Black and Hispanic earners receive 75 cents and 79 cents, respectively, for every dollar of earnings received by the median White earner, median Black and Hispanic earners receive only about 50 cents for every dollar of matching that median White earners receive. For the tax expenditure, comparing workers near the median lifetime earnings for each group, Black and Hispanic workers receive 31 cents and 62 cents for every dollar of the tax expenditure received by White workers, with larger gaps for Black workers being driven by a substantially higher propensity of Black workers to take early withdrawals.

Our focus on racial gaps in retirement wealth accumulation is motivated by two key facts. First,

[1] In 2021, the federal government tax expenditure on defined contribution (DC) retirement accounts amounted to $119 billion (US Department of the Treasury (2023)). In 2020, private sector employers contributed more than $190 billion into these accounts (Department of Labor (2022))–mainly in the form of matching contributions.

[2] We focus on three racial and ethnic groups: non-Hispanic Whites, non-Hispanic Blacks, and Hispanics, who together make up 93% of the individuals in our sample. We will often use "race" to refer to both race and ethnicity, "White" to refer to non-Hispanic White, and "Black" to refer to non-Hispanic Black.

racial wealth inequality in the U.S. is large and persistent; for example, White Americans have, on average, six times the level of wealth of Black Americans, a racial wealth gap that has not changed much since the 1960s (Oliver and Shapiro (1989), Derenoncourt et al. (2022)). There is also a large wealth gap between Hispanic and non-Hispanic White individuals, with the latter being approximately four times wealthier (Sabelhaus and Thompson (2021)). Second, within American households' balance sheets, tax-advantaged retirement accounts are the largest source of financial wealth and the second-largest asset class after housing (Board of Governors of the Federal Reserve System (2021)). Brown (2021) argues that the design of retirement institutions favors activities that are more likely to be carried out by White Americans (retirement saving) and penalizes activities that are more likely to be carried out by Black Americans (early withdrawals). Quantitative evidence on how much employer and tax incentives contribute to racial wealth disparities has been limited due to a lack of systematic data on retirement plan characteristics across racial groups. This paper aims to fill that gap.

We divide our analysis into four parts. First, we document racial gaps in retirement saving contributions and how they vary with worker- and retirement plan-level characteristics. Second, we analyze the contribution of immediate and extended family characteristics to the observed racial differences in contributions among workers with similar individual characteristics. Third, we extend our distributional analysis to dimensions other than race, and study the distributional effects of savings subsidies by family structure, parental background, education, and tenure level. Finally, we develop a microsimulation model to examine the cumulative effect of employer matching and tax subsidies on the distributions of wealth at retirement.

In the first part of the paper, we report large differences in retirement saving contributions across the three groups we study. We find that racial differences in age and income account for only one-half of each of the raw Black–White and Hispanic–White gaps that we document in Figure 1A. This leaves a sizable residual contribution gap: Black and Hispanic workers, respectively, contribute (including employer-matching contributions) 1.1 pp and 0.96 pp less than White workers with the same age and income. We explore the role of other individual-level characteristics that mediate racial savings gaps – such as education, occupation, tenure, and employer. Even after accounting for these mediating effects, gaps remain large at 0.89 pp and 0.44 pp for Black and Hispanic workers, respectively.

What accounts for differences in contributions among workers with similar incomes and individual-level characteristics? In the second part of the paper, we show that racial differences in household composition and parental background account for, respectively, nearly 40% and 50% of the residual estimated gap between Black or Hispanic workers and their White counterparts. Single tax filers, particularly those with dependent children, have lower average contribution rates, and these filing statuses are more common for Black and Hispanic workers. We also find that higher levels of parental income correlate with higher retirement saving (even conditional on our battery of individual-level characteristics, including own income). Black and Hispanic workers tend to have lower-income parents than White workers with similar earnings; therefore, racial differences in parental backgrounds account for part of the residual contribution gap. This finding suggests that the design of retirement saving institutions tends to reward those who have richer parents and contribute more, propagating wealth inequality across generations.

Why does the design of retirement accounts induce lower contributions among Black and Hispanic workers compared with their White counterparts? We find evidence that Hispanic and, to a greater extent, Black workers have stronger liquidity needs and may be more liquidity constrained. In the raw data, White, Black, and Hispanic workers with at least $1,000 in recent contributions have 12.3, 23.3, and 14.5 pp probabilities, respectively, of withdrawing some resources early from their retirement accounts each year. Gaps shrink very modestly when we add controls; Black and Hispanic workers are, respectively, 9.3 pp and 1.3 pp more likely to make an early withdrawal of at least $1,000 relative to White workers with similar worker-level characteristics. The higher likelihood of tapping into these accounts early—despite facing potential tax penalties—indicates a lack of access to alternative sources of liquidity (Coyne et al. (2022)). Consistent with this, Ganong et al. (2020) find that Black and Hispanic households cut their consumption by substantially more than White households in response to a similarly sized income shock. Racial differences in liquidity valuation could also explain why family structure and parental background correlate with retirement contributions. For instance, single-parent households may have stronger liquidity needs than married couples, while workers with richer parents may benefit from access to familial support, while workers with poorer parents may need to retain liquidity to insure themselves or their family (Chiteji and Hamilton (2002), Francis and Weller (2022)). Unlike for other asset classes, such as housing, the illiquid nature of retirement accounts is a policy choice. By subsidizing contributions and penalizing withdrawals, the current institutional design amplifies disparities between more and less liquidity-constrained groups.

In the third part of the paper, we examine differences in contributions across dimensions other than race. We find that, holding income constant, there are marked differences in saving, and so in the receipt of savings subsidies, by dimensions such as family structure, parental income, education, and job tenure. This implies that breaking the link between saving and each of compensation (through matching), and the federal retirement saving tax expenditure could improve retirement outcomes for single parents, children of lower-income parents, those with less education, and those who experience more frequent job separations.

In the last part of the paper, we develop a microsimulation model that uses our data on flows of earnings, employee contributions, employer matches, and early withdrawals to compute wealth and consumption in retirement (taking social security benefits into account). The impact of employer matching and tax subsidies is quantitatively large, accounting for more than 40% of lifetime DC wealth accumulation across all lifetime earnings groups. We then consider revenue-neutral reforms that would redistribute employer-match dollars within each firm and federal tax expenditures across the population so that they are distributed 1) proportionally to earnings and 2) independently of workers' own contribution choices. Within each of the bottom three quintiles of the population earnings distribution, these reforms would increase consumption in retirement by 5 to 10% and also reduce racial DC wealth gaps between Black or Hispanic and White workers by more than 30%.

The first branch of the literature to which we contribute is that concerned with race and wealth in the U.S. The gap between Black and White wealth has been shown to be large (Oliver and Shapiro (1989), Darity and Nicholson (2005)) and, over the last approximately half-century, stable (Derenoncourt et al. (2022)). A rich empirical literature shows that these wealth gaps are larger than can be statistically accounted for by earnings differences (Blau and Graham (1990), Barsky et al. (2002), Altonji and Doraszelski (2005), Wolff (2017), and Kuhn et al. (2020)). The differences in broad measures of wealth that these papers document are also reflected in retirement wealth accumulation (see Ariel/AON Hewitt (2009), Hou and Sanzenbacher (2021), Francis and Weller (2021), Viceisza et al. (2022), and Wolff (2023)), though measures of wealth that include Social Security, due to its progressive nature, display narrower gaps than measures without (Catherine and Sarin (2023), Sabelhaus (2023)). Our contribution to this literature is to study one channel that contributes to wealth inequality by race: the interplay between race and the take-up of explicit subsidies for wealth accumulation that are central to retirement saving institutions in the U.S. Derenoncourt et al. (2022) emphasize that racial differences in rates of return are the dominant factor shaping the lack of convergence of racial wealth gaps over the past 30 years – precisely the period in which DC accounts have emerged as the main vehicle for private retirement savings. Our results shed light on one previously overlooked mechanism generating such differences in effective rates of returns across racial groups, even holding portfolio risk constant.

The second branch of the literature to which we contribute is that concerned with race and earnings in the U.S. Earnings gaps by race have been well documented: Altonji and Blank (1999) offer a comprehensive review of studies to that date, and Bayer and Charles (2018), Chetty et al. (2020), and Derenoncourt and Montialoux (2021) provide more recent evidence. Our contribution is to measure an often-unmeasured component of earnings—the employer match—which gives a wage premium to those who save more.

Third, our paper contributes to the literature that investigates whether features of the policy landscape and economic environment interact with race in contributing to disparities in economic outcomes. This includes research examining whether, and to what extent, racial disparities exist in the implications of policies including welfare (Darity and Myers, 1983, 1987), unemployment insurance (Kuka and Stuart (2021); Skandalis et al. (2022)), mortgage access (Myers Jr (1995), Ross and Yinger (2002), Bhutta and Hizmo (2021)), housing returns (Kermani and Wong (2021)), property tax assessments (Avenancio-León and Howard (2022)), and financial aid for college (Levine and Ritter (2022)). Hamilton and Darity (2017) argue that "if the existing federal asset-promotion budget were allocated in a more progressive manner, federal policies would go a long way toward eliminating racial disparities and building an inclusive economy for all Americans." We quantify how much changing a major component of the US asset-promotion budget, namely the design of retirement savings subsidies, would affect racial and intergenerational wealth inequality.

The fourth line of literature that we contribute to is that on intergenerational persistence in wealth. The correlation in wealth across generations has been well documented (Charles and Hurst (2003)). Recent work emphasizes the importance of heterogeneity in rates of return for cross-sectional wealth inequality (Fagereng et al. (2020)). Our paper draws a link between these two phenomena. While it has long been known that the rich save more (Dynan et al. (2004)), we show that, additionally, the *children* of the rich save more, even conditional on their own earnings. The saving in question here is, by virtue of matching, one with an extraordinary rate of return. This correlation between the resources of one generation and the rates of return availed of by the next will, in general, directly contribute to intergenerational persistence in wealth. This channel also relates to a theme that has been emphasized in the literature on wealth gaps by race in the U.S. Chiteji and Hamilton (2002) and Charles and Hurst (2002) highlight the role of the family in savings decisions, and the direction of intergenerational transfers: Black individuals are both more likely to *provide* support to their parents and less likely to *receive* support from their parents than White individuals.

The paper proceeds as follows. Section 2 discusses the institutional background. Section 3 introduces our new employer–employee linked data set. Section 4 gives our results on racial gaps in retirement saving rates and how they relate to individual characteristics. Section 5 studies the role of household structure, parental background, and liquidity constraints in accounting for these gaps. Section 6 looks at gaps in saving along dimensions other than race. Section 7 uses our data and a microsimulation model to study the distributional impact of the savings patterns that we observe and the retirement saving subsidies that we study on wealth at, and consumption during, retirement. Section 8 concludes.

2 Institutional Background

Defined contribution (DC) plans have become the dominant vehicle through which Americans save for retirement. Sixty percent of U.S. civilian workers now have access to an employer-sponsored DC plan (Myers and Topoleski, 2020). Participants in these plans can make pretax contributions to their accounts (up to a limit on employee contributions of $20,500 in 2022), thereby deferring income taxes to when they retire and when they will (likely) face lower tax rates. In addition to the advantages that this deferral brings, dividends and capital gains are untaxed provided that they remain in the account. Wealth held in DC plans is, due to policy choices associated with the current system, illiquid. Participants generally face tax penalties on withdrawals made before the age of 59.5, though some plans permit borrowing against existing DC balances.

DC plans provide substantial flexibility and discretion to participants in deciding how much to save and in which assets to invest. This structure contrasts substantially with defined benefit (DB) plans, in which the choice facing an employee is typically limited to whether to participate, and *employer* contributions do not depend on any choice that the *employee* makes. The secular shift away from DB toward DC plans in recent years shifts considerable risk related to financing retirement income from employers to employees.[3] Whereas traditional pension plans insure against mortality risk and the lion's share of risks associated with fluctuations in investment returns, DC plans force households to self-insure against these risks.

[3]Only a quarter of civilian workers now have access to a DB pension (Myers and Topoleski, 2020), a share that continues to fall. DC plans are becoming, alongside Social Security, one of the largest sources of income in retirement. Devlin-Foltz et al. (2016) show that, over the past 30 years, the dynamics of retirement wealth have had a moderating impact on overall wealth inequality. They also find, however, that DC wealth is more concentrated than DB wealth.

In the vast majority of plans, the amount that the employer contributes depends on how much the employee chooses to save. Typically, employers match employee contributions at some rate up to a cap. Appendix Figure C.1 shows the full set of matching schedules in our data, the construction of which is described in the next section.

In contrast, the rules governing both employee and employer Social Security contributions are more rigid. Specifically, Social Security payments are financed via non-discretionary FICA payroll tax contributions from both employers and employees on each dollar of labor earnings up to a taxable maximum, and Social Security benefits are computed based on a formula that depends on a worker's earnings history. These benefit amounts are somewhat progressive, implying that low-income workers generally receive larger benefit payments per dollar of payroll tax contributions than higher-income workers in the same cohorts.

As DC plans become more dominant and DB coverage recedes, there is greater scope for individuals' decisions to affect retirement wealth, and employer plan design can amplify the implications of these decisions for wealth inequality. Endogenous DC participation also implies that the benefits paid to employees in the form of matching contributions will not be equally distributed across workers, even among workers with identical earnings. To study the interplay between individual saving decisions and firm matches, we need data that contain both the saving decisions made by individuals and the full match schedules offered by their employers.

3 Data

We form our data set by linking administrative data on the retirement saving and demographics of a large sample of U.S. employees with a newly constructed data set on employer-sponsored retirement plan characteristics. Sections 3.1 and 3.2 describe respectively our employee and employer data.

3.1 Employee data

Our baseline sample is all individuals ever observed in the 2008–2017 American Community Surveys (ACS).[4] We link ACS respondents to other administrative data using protected identification keys

[4] From 2005 to 2019, the average number was over 3.2 million, including a sample expansion from 2010 to 2012. Refer to `https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/sample-size/` for more information on the ACS sample and response rates over time; accessed 11/17/2021.

(PIKs).[5] Some 90%–94% of ACS respondents are successfully assigned a PIK in any given year (Ferrie et al., 2021).[6] Next, we link ACS respondents with their 1040, W-2, and 1099-R filings. The ACS provides individuals' race, year, age, education, gender, occupation, and location at the time of the survey. The 1040 and W-2 filings provide other socioeconomic and demographic indicators, including family structure, employer identification number (EIN), tenure, spousal income, and intergenerational linkages (parental income and parental DC access). We restrict our sample to those between ages 24 and 59 and a half, and our regressions also impose that workers have a modest degree of labor market attachment in the ACS year. Specifically, we impose that the sum of nominal Box 1 wages and deferred compensation exceeds $8,000, which translates to roughly 20 hours per week at the current Federal minimum wage. We also require that individuals make strictly more than $0 in Box 1 wages. Appendices A.2.1 and A.1.3 provide, respectively, detailed overviews of our data build and variable construction.

3.2 Employer retirement plan data

All employers must submit an annual regulatory form (Form 5500) on their U.S. retirement plans to the federal government. Plans with over 100 participants provide narrative descriptions of plan characteristics, including match schedules, vesting schedules, and auto-features. We create a data set by extracting these descriptions from the original free-form text.[7] We do this for the largest 4,800 plans in the US and a random sample of 1,000 smaller plans. These employers cover a substantial portion of the U.S. population; in 2017, 37 million employees were eligible for these large plans, constituting 55% of employees with access to private and nonprofit sector DC retirement plans. Appendix A.2.2 provides further details. These plan-level data, further detailed in Arnoud et al. (2021) and Choukhmane et al. (2023), include information on vesting schedules, auto-enrollment, and crucially for our question, match schedules. These match schedules are typically concave functions of employee contribution rates, often linear up to a threshold. Figure C.1 illustrates the observed variation in match schedules in our 2017 employer-sponsored plan-level data.

To match the retirement plan data with our employee data, we use a multistage fuzzy matching

[5]PIKs are assigned by a probabilistic matching algorithm that compares the characteristics of records in Census, survey, and administrative data to those in a reference file constructed from the Social Security Administration Numerical Identification System and other federal administrative data. PIKs correspond one-to-one with SSNs and so allow us to link individuals over time and across data sources. For more information, see Wagner and Layne (2014).

[6]As noted in Bond et al. (2014), there is some selection into linkage, for example by age, race, and citizenship status. However, we do not believe that the magnitudes of these differences will bias our estimates substantially. For example, in 2010, the linkage rate for Black ACS respondents was 91.4%, compared to 93.5% for White respondents.

[7]`https://www.dol.gov/agencies/ebsa/about-ebsa/our-activities/public-disclosure/foia/form-5500-datasets`.

procedure with numeric identifiers such as the EIN, telephone number, name, and address fields. We impose two key restrictions: i) the employer must use the same matching formula for all employees and ii) the firm-level employer share of contributions (the ratio of firm-level aggregate employer match divided by the sum of firm-level aggregate employer match plus employee deferred compensation) for each employer must be within 15 pp of our W-2 imputation. Note that while employers include firms, hospitals, non-profits, and other non-firm employers, "firm" and "employer" are used interchangeably throughout this paper.

3.3 Samples

We define three main samples: i) our "full ACS sample", ii) our "matching sample" of individuals for whom we have employer-level retirement plan data, and iii) the "parent-matching sample", which is the sample for whom we can link individuals to their parents. We start with the full ACS cross-section of approximately 12,480,000 unique individuals. The "full ACS sample" contains the observations in the ACS cross-sections for whom we have data on all individual-level characteristics. Next, the "matching sample" corresponds to the subset of ACS respondents for whom we have collected employer-sponsored retirement plan information from Form 5500 filings. This serves as the primary sample in most of our analysis. Finally, the "parent-matching sample" corresponds to the subset of the "matching sample" for which we can link respondents to their parents, and who are in the 1978–1992 birth cohort. Appendix A.3 provides more details on the different samples.

We distinguish the samples by our sampling procedure. All three samples include ACS individual-level survey data, and thus follow ACS survey procedures. However, our matching and parent matching samples effectively sample from two populations, first from the U.S. population via the ACS and then sampling employees at certain employers from the employer population. We thus combine ACS and employer-level weights. In contrast, our full ACS sample, which is not matched with employer retirement plans, simply uses the ACS weights. See Appendix A.2.3 for a detailed explanation of the sampling and weighting procedures.

3.4 Retirement savings outcomes

Our four primary measures of saving and withdrawals are: i) **Employee contributions**: real deferred compensation reported in Box 12 of the W-2 tax form. This amount generally corresponds to contributions to an employer-sponsored contribution plan (such as a 401(k)). We define the employee contribution *rate* as a percentage of salary using the ratio of the employee contribution reported in Box 12 to the sum of the taxable wage reported in Box 1 of the W-2 form and the Box 12 employee contribution. ii) **Participation**: is a dummy equal to one if the individual makes a positive contribution to a retirement savings plan. iii) **Employee plus employer matching contributions**: the sum of the employee contribution and the employer match contribution we can calculate using match formulas gleaned from Form 5500 filing. iv) **Early withdrawals**: we create a dummy equal to 1 if an individual between the ages of 25 and 54[8] has a positive distribution from a retirement account reported in tax Form 1099-R. Appendix A.1.2 gives further details on variable construction.

4 Racial Gaps in Retirement Wealth Accumulation

In this section, we document the following facts about the racial gaps in retirement savings rates: they are large, get amplified by employer matches, persist even after we condition on a rich set of individual characteristics, and are larger in subgroups in which White workers save more.

4.1 Gaps in retirement savings by race are large, and employer matching contributions amplify the savings and total compensation differences

We begin by characterizing some basic facts about the distribution of employer and employee contributions in the raw data. Figure 1A reports the ratio of average contributions to average labor income. In our "matching sample" (which is our primary sample), White workers save on average 4.2 pp of their labor income per year in employee contributions to DC retirement accounts, while Black (Hispanic) workers save 2.4 pp (2.6 pp). This raw gap is large, implying that the savings rate of Black (Hispanic) employees is 43% (38%) lower than that of White employees. Figure 1A also illustrates the additional impact of matching. White employees gain an additional 2.1 pp of salary, worth $1,974 a year on average, from employer matching contributions. Meanwhile, Black (Hispanic) employees receive an increase of only 1.4 pp (1.5 pp) of salary, i.e., $857 ($993) a year from employers. Altogether, White workers' DC inflows average 6.3 pp of their labor income, while Black (Hispanic) workers' average 3.8 pp (4.2 pp). For the rest of the main text, unless otherwise specified, we refer to contribution rates as the sum of employee and employer-matching contributions.

These differences in saving rates imply substantial gaps in the component of compensation com-

[8] After this age, withdrawals on separations from an employer mean that there is no tax penalty.

ing from matching benefits. In Figure 1B, we compare the racial disparities in employer matching with disparities in other employee compensation (i.e., wages plus deferred compensation). We characterize these gaps for workers who are around the median of the labor income distribution by race in each year. Figure 1B plots the average earnings for workers between the 45th and 55th percentiles—a quasi-median—of earnings for their specific race and normalize it to $1 for the level of earnings earned by White workers near the median. In our data, a Black (Hispanic) worker near the median earns 75¢ (79¢) for every dollar earned by a White worker near the median. While our sample differs somewhat from that in other studies (in that we drop some workers with low earnings and focuses on firms with DC plans) our results are largely consistent with findings in the most recent literature on the gaps in labor income across races (Bayer and Charles, 2018; Derenoncourt and Montialoux, 2021). Figure 1B documents the average employee matching benefits received for this same group of workers, again expressing values relative to the level accruing to White workers. Gaps in employer matching are much larger than the gaps in earnings that have been the focus of the literature: Black (Hispanic) workers near the median of their race-specific income distribution earn 47¢ (52¢) for every dollar of matching that their White counterparts receive.[9]

These differences of 1.6–1.8 and 0.7-0.8 pp in own and employer contributions, respectively, are quite large in relation to the average rate DC contribution rates in our sample and the typical flow of savings in aggregate data. For instance, the Bureau of Economic Analysis reports an average personal saving rate of approximately 6% of disposable income between 2005 and 2019. The tax treatment, as we will quantify in Section 7 further amplifies these discrepancies in terms of the value of these contributions at retirement. As a result, these differences in behavior can add up to very large differences in racial wealth accumulation, as we quantify in greater detail below.

4.2 Differences in worker-level characteristics account for a significant share of racial contribution differences

Given that racial groups differ along a number of observable and unobservable dimensions, we use regressions to explore the extent to which differences in economic characteristics across groups help to account, in a statistical sense, for the gaps documented above. We interpret these results not as explaining away part of the racial contribution gap but rather as providing indicators of different

[9]It is not possible to evaluate the corresponding gaps in retirement incentive–related tax expenditure without the use of a model of saving and withdrawals over the lifecycle. Section 7 provides such a model. We find there that, for each dollar of this tax expenditure received by the median White earner approximately 31 (62) cents is received by the median Black (Hispanic) earners. Details are deferred to that section.

channels that mediate racial disparities in saving rates. We leverage the rich set of data on the demographic and economic characteristics of employees with access to a DC account to estimate linear models for worker i of the form:

$$y_i = \alpha + \beta race_i + X_i'\delta + \epsilon_i, \tag{1}$$

in which we progressively add observable characteristics such as dummies for age (in five-year bins for ages 25–29 to 55–59.5), year, deciles of labor income (i.e., deflated W-2 income plus deferred compensation), education group (i.e., did not receive a high school diploma or equivalent, high school graduate or equivalent, college degree, and graduate degree), gender, occupation, county, employer identification number (EIN), and tenure bin. To ensure that our estimates are representative of the population of firms filing the long form of Form 5500, we use a composite weight that accounts for differences in sampling frequencies in the ACS and our likelihood of including a firm in our sample of DC retirement plans. We cluster the standard errors at the employer's EIN level. For reference, Table 3 shows coefficients from a specification that includes the full set of individual characteristics as well as family structure and spousal income.

Equation (1) is fairly standard in the literature on wage gaps (see, e.g., Cahuc et al., 2014, Ch. 8). The vector $race_i$ includes indicators for Black, Hispanic, Asian, Native American, Pacific Islander, and Two or More racial groups, and the omitted category is White workers. Our analysis restricts attention to the three largest racial groups in the U.S.; therefore, the coefficients we report are the elements of β on the dummies for Black and Hispanic group membership. In Figure 2, we plot the estimated $\hat{\beta}$s using the data from our primary sample, where we start from the univariate version of Equation (1) and, at each successive point, add an additional group of variables until the model becomes fully saturated.[10] In each step of this "regression cascade," β captures differences in the mean of y_i that cannot be accounted for by $X_i'\delta$; hence, the addition of a new variable shrinks the gap only if it incrementally predicts y_i and there is a correlation between the variable and group membership.[11] Before discussing findings from this analysis, we recognize it is often unclear the extent to which one should partial out many of the characteristics that we consider here when assessing the magnitudes of racial gaps, especially given that some of the differences in

[10]Fully saturated in the context of this section means that the regression includes indicators for year, age, income, education, gender, occupation, county, EIN, and tenure. While Figure 2 also reports estimates from regressions which include household and family characteristics, we defer our discussion of these controls until in Section 5.1.

[11]In Figure C.5 in Appendix C, we visualize these relationships more directly. Specifically, we summarize the distribution across age, income, education, and spousal income bins (which we discuss in Section 5.1) alongside the coefficients associated with bin membership coming from the saturated regressions reported in Table 3.

the distribution of X_i across racial groups may reflect racial barriers faced by Black and Hispanic workers.[12] We emphasize that changes in β estimates from inclusion of a new variable provide incremental information about the joint distribution of X_i, race, and savings rates.

In Figure 2A, the main outcome variable is the employee contribution to the DC retirement plan plus the employer matching rate as a percentage of income, though we also display the component coming from the employee's own contribution rate in the darker color. Collectively, the main economic characteristics that we consider (columns through "Tenure" in Figure 2A) reduce the estimated Black-White and Hispanic-White gaps from 39% (34%) (as a share of the average contribution rate for a White worker) to 14% (7%). Nonetheless, Black (Hispanic) employees still contribute nearly 1 pp (0.5 pp) less than their White colleagues with similar observables—i.e., workers with the same age, income, education and gender, working in the same occupation and firm, with similar job tenure, and living in the same county. Figures 2B and C consider the breakdown into the intensive (savings rate conditional on participation) and extensive (participation rate) margins, respectively. While gaps persist on both the intensive and extensive margins, racial differences in worker-level characteristics can account for a large part of the extensive margin participation gap while most of the intensive margin contribution gap remains unaccounted for.

Next, for each of the individual-level characteristics that we include in this analysis, we discuss the following: potential economic rationales for why the characteristics may impact DC savings rates, the relationship between these variables and average savings rates, and the extent to which they impact the racial gaps in contribution rates. For part of this discussion, we examine the estimated coefficients from our most detailed multivariate specifications, which include all variables and are reported in Table 3.

Year: Recent years have seen a substantial evolution in the DC landscape (e.g. the growth of auto-enrollment). To account for these, as well as savings differences over the business cycle, we include year fixed effects. Their inclusion has little impact on the estimated gaps since the composition of these racial groups was fairly stable over this time period. Appendix Figure C.7 further shows that gaps are fairly similar across calendar years.

Age: Age is an important driver of retirement saving: financing consumption in retirement is likely to be a central financial objective for older workers, whereas younger workers face a number of other competing savings objectives. Black and Hispanic workers are younger on average than

[12] See, for example, Neal and Johnson (1996); Lang and Manove (2011); Carneiro et al. (2005) for a discussion about test score and education controls in racial wage gap regressions.

White workers, and so understanding the extent to which age differences account for the gaps we observe is important. We find the expected relationship that savings rates are increasing in age (see, e.g., Gourinchas and Parker, 2002): relative to those aged 25-29, those aged 30-34 have saving rates that are 0.6 pp higher and those of the 55-59.5 group are 2.6 pp higher. Accounting for age differences and including year controls reduces the estimated Black–White (Hispanic–White) gap from 39% (34%) (as a share of the average contribution rate for a White worker) to 36% (29%).

Income: Income is the characteristic which has been a traditional focus of the literature (and legislation) on distributional analysis of the retirement system. It is well established that the rich save more (Dynan et al., 2004) and there are many reasons why this would be the case. Social Security replacement rates benefits decline in income, the tax benefits are highest for those with the highest income (Congressional Budget Office, 2021), income risk tends to decline with income over most of the distribution outside of the top decile (Guvenen et al., 2014), and financial literacy is typically increasing in income (Lusardi and Mitchell, 2014). Furthermore, there are well-established differences in the distribution of income across races (see Figure 1 and Appendix Figure C.5B).

We construct income groups by sorting workers into deciles of labor income within each calendar year and age bin. Table 3 shows that average contribution rates increase across the bottom nine deciles, with employees in the bottom decile contributing 1.6 pp less than workers in the fifth decile. Workers in the top income decile contribute slightly less than those in the ninth decile – this reflects the impact of tax limits on maximum contributions which are most likely to bind for those with the highest incomes. Income gradients are especially strong with respect to the decision on whether to participate or not[13] but also have an association with saving rates, conditional on participation. The measured racial contribution gap (relative to the average contribution rate of a White worker) between Black (Hispanic) workers and their White counterparts decreases from 36% (29%) to 17% (15%) when comparing workers in the same income bin. Figures 2B and 2C show that the impact of income on estimated contribution gaps is particularly large on the extensive margin.

Education: Education attainments could affect saving beyond their correlation with income levels, through several channels: lifecycle trajectories in expected income levels and income risk vary with education, and financial literacy is increasing in education. We consider the role of the highest degree attained, which we capture via four dummies for less than high school, a high school degree, a college degree, and a graduate degree. We find a strong relationship between educational

[13] Column 3 of Table 3 shows that, relative to workers in the fifth income decile, workers in the bottom and top deciles are 24 pp less and 15 pp more likely to participate, respectively, conditional on all other controls.

attainment and savings. Conditional on other worker-level characteristics, those without a high school diploma or equivalent contribute 0.19 pp less to a DC account than those with a high school diploma, 0.83 pp less than those with a college degree and 1.2 pp less than those with a graduate degree. Accounting for racial differences in education attainments has a modest effect on the estimated Black–White contribution gap (the gap as a share of average White contribution falls to 16% from 17%), but these education attainments account for a larger share of the Hispanic–White gap, which decreases to 11% from 15% after accounting for differences in education attainment. This finding reflects the fact that a larger share of Hispanic workers have lower levels of educational attainment relative to Black and White workers (see Figure C.5C).

Gender: Men and women may save different amounts for a variety of reasons such as differences in lifecycle earnings profiles (Goldin, 2021), risk preferences, life expectancy, and/or expected retirement benefits (Barber and Odean, 2001; Watson and McNaughton, 2007). We find that, conditional on the full set of characteristics we include, female workers are 4.3 pp more likely to participate and contribute 0.55 pp of salary more to DC accounts than men. Given, though, that gender ratios are similar for workers across the racial groups we consider, gender has little impact on the estimated contribution gaps.

Occupation and County: Occupation may be relevant for savings, as it can correlate with expected future earnings, income risk, financial literacy (indeed, we consider an occupation-based proxy for financial literacy below), and potential differences in risk or time preferences. Perhaps surprisingly, the inclusion of occupation fixed effects has little impact on estimated racial contribution gaps. Racial composition differs across space, which may correlate with various factors such as the cost of living in retirement, so we additionally absorb county fixed effects. We find that absorbing county fixed effects shrinks the Black–White (Hispanic–White) estimated gap from 16% (10%) to 14% (8%) relative to the average White contribution rate.

Employer (EIN): Our data allow us to absorb EIN fixed effects, which allows us to identify racial contribution gaps among coworkers within the same employer. In addition to a number of economic characteristics that may differ across firms (for example, expected income trajectories, and employment stability), a natural possibility is that workers sort into firms that differ in terms of the quality of the retirement benefits that they offer.[14] For example, there is substantial heterogeneity

[14] We test a simple aspect of this sorting hypothesis in column 8 of Table 3. We run a version of our main specification with everything except the EIN fixed effects where the main dependent variable is the aggregate matching rate at the firm level (average employer match/average labor income) and examine whether Black and Hispanic workers are more likely to work at employers with lower average matching rates. The differences in these average matching rates are fairly small at +2 bp and -4 bp for Black and Hispanic workers relative to White workers, respectively.

across firms in the generosity of matching incentives, the nature of vesting schedules, and auto-enrollment and other default policies. Absorbing EIN fixed effects allows us to hold many of these features constant. We measure virtually no additional impact on the Black–White gap, while the Hispanic–White decreases slightly from 8% to 7% as a share of the average contribution rate of White worker (driven by a decline in the extensive-margin gap).

Tenure: The final economic characteristic that we consider is job tenure, which we split into bins for 1, 2, 3, and 4+ years. Tenure may relate to saving through its correlation with employment risk (e.g., Farber, 1994, shows that the probability of job separation decreases for workers with higher tenure), the probability that a worker's contributions will vest, and workers' awareness of plan benefits, among other channels. Compared to employees with less than a year of tenure, employees with one year of tenure contribute 0.47 pp of salary more to a DC account, while employees with at least three years of tenure save 1.8 pp more. Taking racial differences in tenure into account has, however, little effect on the residual contribution gaps.

Taking Stock. We find that workers who are older, higher income, female, more educated, and have longer tenures contribute substantially more toward retirement and, thus, receive much more in employer matching benefits. Accounting for differences across workers in these observable characteristics can account, in a statistical sense, for part but not all of the racial gaps that we document. We interpret the role of these different characteristics as channels mediating racial disparities in retirement contribution rates. Figures 2B and 2C illustrate the intensive margin and extensive margin effects: our estimates reflect a mix of both effects.

Before proceeding, it is useful to address two additional potential concerns. First, in the analysis above, individual characteristics are accounted for using an additive specification. To evaluate whether this additivity is concealing consequential interactions between characteristics, we rerun the analysis in the first 5 layers of the cascade by reweighting the cells based on observables. Figure C.3 in Appendix C shows a cascade similar to that in Figure 2A for all the individual characteristics up to gender, and the qualitative lessons are unchanged. For the remaining analysis, we discuss the results based on the linear model. A second potential concern relates to the representativeness of our sample. In Figure C.4 in Appendix C, we conduct the same regressions for the full ACS sample, and the baseline results are not meaningfully affected.

4.3 Other potential factors contributing to differences in retirement wealth accumulation

While we discussed the contribution of several worker-level characteristics to the estimated racial contribution gaps, other factors could matter for the observed differences in retirement contributions across racial groups. In this subsection, we discuss briefly some of these potential factors.

Retirement plan-level characteristics. Black and Hispanic workers may contribute less than their White counterparts if they are more likely to work at employers who do not sponsor a DC plan or have access to plans with different or less desirable features (i.e., matching formula, vesting schedule, or auto-enrollment). In Appendix Figure C.2 we show that differences in access to an employer-sponsored retirement plan are small, especially after controlling for worker-level characteristics. In Appendix Figure C.2B, we find that on average Black and Hispanic employees have access to plans with less generous employer contributions, however, this difference is no longer significant for Black employees and is significant but very small in magnitude for Hispanic workers once we adjust for individual-level characteristics. In Appendix Figure C.4, we show that contributions gaps are just as large when restricting the sample to workers who are fully vested in the plan (that is workers who, if they separate, would retain all previously-received employer contributions), suggesting that these differences are not driven by racial differences in the risk created by the vesting schedule. Finally, comparing employees hired before and after the adoption of auto-enrollment, we find that auto-enrollment raises the average level of participation but has little to no effect on the racial contribution gaps conditional on characteristics (Figure 2A). Taken together, these results suggest that, conditional on worker-level characteristics, retirement plan characteristics have little effect on racial contribution gaps.

Financial literacy and life expectancy. There is a large empirical literature establishing the importance of financial literacy and life expectancy for retirement saving decisions (see Lusardi et al. (2017) and De Nardi et al. (2009) for examples respectively). Our data does not permit us to directly measure the contribution of these factors to racial contribution gaps. We do not have any measures of financial literacy at an individual level but can define a proxy of financial literacy based on the knowledge content of different occupations. Using this measure, and with the caveat that our proxy is only at the occupation level, we find that, if anything, racial contribution gaps are largest for workers predicted to have higher levels of financial literacy (see Appendix Figure C.18). On life expectancy, our conditioning on age and income capture much of the variation in life expectancy. While life expectancies for Black Americans are lower than those for White Americans, who in turn have lower expectancies than Hispanics, Chetty et al. (2016) show that differences by race are small when comparing individuals with similar income levels.

4.4 The racial gaps are larger in groups with higher average levels of retirement saving contributions among White workers

Thus far, our analysis has focused on understanding differences in average contributions by race. Here, we examine the heterogeneity in the size of the racial savings gaps across workers with different characteristics. More precisely, we augment our baseline estimating Equation (1) as follows:

$$y_i = \alpha + \beta race_i \times Z_i + X_i'\delta + Z_i'\gamma + \epsilon_i, \tag{2}$$

where Z_i is a vector of dummies for an additional category of interest. We summarize the main takeaways from this analysis here and present more detailed heterogeneity results in Appendix Figures C.7-C.18 (including raw differences along the different observable characteristics).

Heterogeneity by Age and Income. Figure 3 illustrates pattern of contributions by age and income across racial groups after controlling for other characteristics such as occupation, education, and EIN (see Appendix Figures C.8 and C.9 for similar patterns without controls). Across all groups, contributions increase with age and income, but Black (Hispanic) workers aged 40–44 (35–39) contributes only as much on average as White workers aged 25–29. Furthermore, racial savings gaps increase with income. We observe no differences in contributions for individuals in the bottom decile of incomes (i.e., contributions are uniformly low). In contrast, we find Black (Hispanic) workers in the 9th decile of income save 1.7 pp (0.98 pp) less than their White counterparts.

Broader patterns of heterogeneity. We estimate the heterogeneity in racial savings gaps along six additional dimensions: education, gender, tenure, financial literacy, generosity of employer matching contributions, and health insurance status. Figure 4 summarizes the results from this heterogeneity analysis results in the fully saturated model.[15] The broad pattern is one in which the higher are the White saving rates for the group in question (on the horizontal axis), the larger are the gaps (on the vertical axis). Conversely, the racial disparities in retirement savings tend to be narrower among groups who save less for retirement. These disparities widen as individuals gain the resources and capability to contribute more towards their retirement savings. The figure shows

[15]Note that, for specifications that are homogeneous within occupation (e.g., financial literacy) or EIN (e.g., employer matching generosity), the fully saturated model does not include the corresponding fixed effects.

that workers who are more educated, are female, have longer tenure, are more financially literate, face more generous matching subsidies, and have private health insurance tend to contribute more to retirement plans, and these are also the groups for whom racial disparities in contribution are more pronounced. We give more detail on patterns of heterogeneity in Appendix A.5.

5 Potential Drivers of Racial Differences in Contributions among Workers with Similar Individual-Level Characteristics

The previous section documented that a significant share of the difference in contributions across racial groups is mediated by differences in age, income, and other individual characteristics. Still, significant contribution gaps persist even after accounting for a large set of individual-level characteristics. Black (Hispanic) workers contribute 14% (7%) less than White workers with similar individual-level characteristics. In this section, we examine how household structure and parental background impact saving levels across races, and we discuss the role of liquidity constraints.

5.1 Household and extended family characteristics explain a significant share of the residual contribution gap

In this section, we explore the role of family structure and parental resources in retirement saving decisions. We find that racial differences in these characteristics can account for nearly half of the residual gap in contributions gaps remaining after partialing out individual-level characteristics.

5.1.1 Family structure and spousal resources

The incentives to save can vary with the size and composition of a worker's household. For instance, the marginal utility of a given level of consumption may be higher for workers who have larger families with more dependents. Further, dual earner households may be better diversified and, therefore, more willing to invest in an illiquid retirement account. Oliver and Shapiro (1989) found marked gradients in wealth by family structure and argued that these patterns are relevant for understanding racial wealth inequality. Here, we evaluate the extent to which savings rates vary by the structure of the household (i.e., number of adults and/or the presence of dependent children), as well as the level of spousal income, if any.

We measure household composition by dividing households into five groups based on an individual's tax filing status. Four of these groups represent single or married filers with or without dependent children. A fifth group is formed of those who do not file taxes and for whom information on marital status and children is missing. Nonfilers and single tax filers, particularly single filers with children, tend to have lower contribution rates across all three racial groups, even after we account for worker-level and retirement plan characteristics (as is illustrated in Figure 5A).

We measure spousal resources with 12 indicator variables, one for each age-adjusted decile of spousal income, one for spousal income of zero, and one for observations with missing spousal income, for instance, because the worker is a single filer (see Appendix Figure C.5D for details). Table 3 reports regression coefficients for each of these indicator variables and shows that the spouses of high earners save more: workers with spouses in the top decile of spousal income contribute 0.78 pp more than otherwise similar workers with spouses in the bottom decile.

These results show that family composition and the presence and level of spousal income are important determinants of saving. In each case, Black and Hispanic workers are more likely to have characteristics associated with lower saving: they are, respectively, 3.5 and 2.4 times more likely to be single filers with children than are White workers and, when married, they have lower-income spouses than otherwise similar White workers. Consequently, accounting for differences in household composition and spousal income reduces the measured racial contribution gaps. Figure 2 shows that doing so reduces the estimated Black–White (Hispanic–White) gap from 14% (7%) to 11% (6%) as a share of the average contribution rate of a White worker. These increments are substantial since they follow *after* the mediating effects of individual-level characteristics (such as income, education, and occupation) have been accounted for.

5.1.2 Parental resources

In this sub-section, we investigate the role of parental income in retirement saving. An advantage of our data is that we can link individuals to their parents for a subsample of younger individuals (born between 1978 and 1992) who were claimed as dependent by their parents at age 16 (see Section 3.3 for more details). While the broad patterns we have documented remain true in this sub-sample of younger workers, there are some differences in magnitudes. Across all racial groups, contribution rates are lower in this younger sample; thus, the gaps we estimate are slightly smaller: Black (Hispanic) workers' employee contributions are, on average, 1.3 pp (0.9 pp) of earnings lower compared to their White counterparts. Employer matching increases these contribution gaps to 2.0 pp (1.4 pp). As with the full sample, accounting for individual and household characteristics shrinks these estimated gaps in contributions (i.e., employee plus employer-matching contributions): the residual gap in contributions between Black (Hispanic) workers and their White counterparts after accounting for individual characteristics is 0.70 pp (0.37 pp) and after additionally accounting for family structure and spousal income is 0.57 pp (0.32 pp). These patterns are shown in Panel A in Figure 6.

We find that higher parental income levels are associated with higher retirement contribution rates, even after accounting for differences in own earnings and other individual and household characteristics. Panel B of Figure 6 shows coefficients on parental income deciles from our fully saturated regression. It shows that the children of the rich save more: workers with parents in the top parental income decile contribute approximately 0.7 pp more than those with parents in the bottom half of the parental income distribution. One potential channel consistent with these patterns is intergenerational insurance. Richer parents can support their children financially and insure them against shocks (Fagereng et al., 2023), while poorer parents may require the financial assistance of their adult children (Chiteji and Hamilton (2002), Francis and Weller (2022)). The extent to which one's relative can provide financial insurance (or require financial support) may affect workers' decision to save in an illiquid account.

This association between parent income and own saving is relevant for the racial saving gap—Panel C of Figure 6 shows the average income of parents for workers of each race in a given income decile. A White worker in the middle-income decile has parental income (averaged over both parents if present in the household) of approximately $90,000, on average. For Black and Hispanic workers in the same income decile, the average parental income is approximately $50,000. Panel D of Figure 6 further illustrates the difference in the distribution of parental income by plotting the relative shares of workers falling into different deciles of the parental income distribution by race.

Taken together, these two facts–that the children of the rich save more, and that the parents of White workers are richer than those of Black and Hispanic workers–imply that parental income can play a mediating role in the racial savings gap. We quantify this effect in Panel A of Figure 6. Including indicators for each decile of parental income at age 16 reduces the estimated Black–White (Hispanic–White) gap from 0.57 pp (0.32 pp) to 0.44 pp (0.19 pp). Put differently, it reduces the residual contribution gap (i.e., the estimated gap that remains after accouting for the part mediated by individual- and family-level characteristics) by 23% and 40% for, respectively, Black and Hispanic workers relative to their White counterparts.[16]

[16] We also evaluate the importance of including a dummy for parents having contributed to a DC account, a proxy for familiarity with and exposure to these accounts. This does not affect the size of the residual contribution gap.

5.2 Racial disparities in early withdrawals highlight the role of liquidity constraints

Black and Hispanic workers may choose to forgo the generous subsidies associated with retirement contributions because they face stricter liquidity constraints. Coyne et al. (2022) highlight that the propensity to tap into retirement accounts early—despite the potential tax penalties—can serve as a measure of differences in liquidity valuation. Those who are more likely to take an early withdrawal reveal a high preference for liquidity and a lack of access to alternative sources of liquidity. We find that Hispanic, and to a greater extent Black, Americans are more likely to withdraw resources early than are White workers with similar worker-level characteristics.

While employer-sponsored retirement savings plans are designed to be a vehicle for saving to finance consumption in retirement, individuals are allowed to access these resources early. These early distribution options are, however, discouraged by the tax code. Unless the distribution qualifies for an exception, withdrawals before the age of 59.5 are subject to a 10% tax penalty and, prior to 2020, additionally trigger a minimum six-month suspension from contributing to the plan. Despite these restrictions, early withdrawals are common: Goodman et al. (2021) find that flows out of DC plans and IRAs over a 12-year period accounted for over 20% of the value of flows in.

We measure early withdrawal rates using data from the 1099-R tax forms of individuals older than 25 and strictly younger than 55.[17] We define individuals as taking an early withdrawal if we observe a withdrawal of at least $1,000 (in 2017 dollars) in the calendar year following the ACS year.[18] Due to data limitations, we cannot distinguish between penalized early withdrawals—those subject to the 10% tax penalty—from nonpenalized hardship distributions. Because those who have never contributed cannot take early distributions we restrict the sample to individuals who have made at least $1,000 of retirement contributions over the preceding 4 years. We discuss this and other sample restrictions and variable definitions in Appendix A.

Before the of age 55, on average, 12.3% of the White retirement savers in our sample take an early distribution each year, compared to, respectively, 14.5% and 23.3% of Hispanic and Black savers, respectively (Table 1). The Black–White gap is striking: Black retirement savers are nearly twice as likely as their White counterparts (i.e., have a 90% higher probability) to withdraw at

[17] Early withdrawals are not penalized for individuals who separated from their employer at or after age 55 or for any individuals older than 59.5.

[18] Employers are allowed to implement an automatic cash-out for terminated employees with a balance smaller than $1,000. Therefore, early withdrawals smaller than $1,000 may not reflect an active decision of the individual. Our rationale for looking at the year after the year a worker is included in our main regression sample is to allow for the possibility that earnings go to zero (i.e., we do not want to condition on workers being employed).

least \$1,000 early in a given year. The disparity is also large, albeit much smaller, for Hispanic savers, who are 21% more likely to take an early withdrawal than their White counterparts. In Panel A of Figure 7, we plot a cascade similar to that in Figure 2A, but the outcome variable here is an indicator for an early withdrawal. Accounting for differences in income decreases these racial withdrawal gaps to 84% and 16%, respectively, for Black and Hispanic individuals. Including EIN fixed effects, which capture potential differences in hardship distribution rules across employers, can explain some of the residual racial differences in withdrawals, but the gaps remain large even after we include the whole set of individual characteristics.

The propensity to take an early distribution is higher when liquidity needs are higher. To illustrate this, we sort workers into 20 ventile bins based on the growth rate of income between year t (the year in which the respondent fills out the ACS and in which we measure savings gaps) and year $t+1$. Figure 7B reports the average propensity to take an early withdrawal of more than \$1,000 by race across the twenty income growth bins. Those who experience large income declines are more likely to tap into their retirement assets early: 52% (41%) of Black (Hispanic) workers in the bottom ventile of income growth take an early withdrawal of at least \$1,000, compared to 35% of White workers.[19] Other proxies of stricter liquidity constraints, such as having a larger expenditure share dedicated to housing costs, are also correlated with higher levels of early withdrawals (see Appendix Figure C.15 for details).

We interpret these large differences in the propensity to take an early distribution as evidence that Hispanic and, to a greater extent, Black savers have stronger liquidity needs and are more liquidity-constrained than White savers with similar incomes. Consistent with this interpretation, Ganong et al. (2020) find that Black and Hispanic households cut their consumption substantially more than White households following a similarly sized income shock. Racial differences in liquidity valuation could also explain why family structure and parental background correlate with retirement contributions. For instance, single-parent households may have stronger liquidity needs than married couples, and as shown in Panel B of Appendix Figure 5, across all three racial groups, single filers with dependent children are more than 5 pp more likely to take an early withdrawal in a given year than dual filers without children. Similarly, those with richer parents may benefit from easier access to liquidity through familial support, and as shown in Panel B of Appendix Figure

[19] Very high and very low values of income growth tend to correlate with job separations. Appendix Figure C.6 shows that the probability of remaining at the same main employer between t and $t+1$ is an inverse U-shaped function of the earnings growth rate. Around 55% of workers in the bottom ventile of earnings growth switch jobs (which includes transition into non-employment and zero earnings realizations).

C.14, the racial gaps in early distributions shrink for those with parents in the top decile of the parental income distribution.

Binding liquidity constraints could also explain the lower levels of participation and contributions among Black and Hispanic workers. A partially illiquid retirement account is a less desirable savings vehicle for those facing more acute liquidity needs. This is consistent with evidence from Mitchell et al. (2007) that access to a loan option increases participation in 401(k) plans and evidence from Briere et al. (2022) that workers avoid less liquid investment options in French retirement plans. Unlike other asset classes, such as housing, the illiquid nature of retirement accounts is a policy choice. Early withdrawals are penalized by the tax system and in most plans, 401(k) loans—which provide liquidity to currently employed participants—must be fully repaid at job separation in most plans, a time when liquidity needs are heightened. By subsidizing contributions and penalizing withdrawals, the current institutional design ties a worker's total compensation and tax liabilities to her ability to forgo immediate access to funds, furthering disparities between more and less liquidity-constrained groups.

6 Gaps in Retirement Wealth Accumulation on Dimensions Other than Race

Our primary focus in this paper is to document and better understand savings gaps by race. These differences in saving rates generate differences in remuneration across workers and the incidence of tax subsidies provided by the government.

In Section 4.2, we discussed the contribution of a number of individual characteristics to our estimates of residual racial contribution gaps. In this short section, we emphasize the extent of their independent association with saving, and therefore the extent of their association with saving incentives. Just as the matching and tax subsidies associated with the current system will disproportionately accrue to White workers relative to their Black and Hispanic coworkers, these subsidies will also disproportionately accrue to other groups with higher saving rates.

Figure 8 shows coefficients which we obtain from the following model

$$y_i = [D_i \otimes Z_i]'\omega + X_i'\delta + \epsilon_i, \tag{3}$$

where D_i is a set of indicators for income deciles and Z_i is a vector of dummies for an additional characteristic. As before, X_i captures controls for year, age, gender, occupation, education, county, EIN, and tenure (where we omit Z_i from inclusion in X_i where applicable). As illustrative examples, we will consider four characteristics: education, job tenure, family structure, and parental income. In each clustered column chart, different shading represent group categories, and each set of clustered columns corresponds to a different income decile. The main coefficients of interest are in ω, which reveal differences in contributions in a given income$\times$group bin relative to the omitted category (which is indicated with a dashed vertical line) and a coworker with similar Xs.

Taking education first, even for workers with similar income levels, we find that the workers with higher levels of educational attainment save more—the gaps are quite large, especially in the top half of the income distribution.[20] Gaps are also large by tenure, which is correlated with both job stability and likely awareness of the matching benefits that a firm offers. The bottom row of Figure 8 considers two measures of family background, family structure (bottom left) and parental income (bottom right). Since non-filers and single parents tend to save less, they will tend to participate less and therefore enjoy fewer matching and tax subsidies relative to their coworkers. Finally, conditional on own income, those with richer parents save more. These results suggest that, among workers with the same earnings, the current system will tend to redistribute towards those with more education, those with higher job tenure, dual filers, and those with richer parents.

Our final section will focus on differences in lifeycle aggregates by earnings, race and parental income. The analyses in this section serve to emphasize that, more generally, the system of retirement incentives redistributes from workers who, all else equal, save less to those who save more and that saving correlates in systematic ways with many economic and demographic characteristics.

7 Aggregate Effect of Retirement Savings Subsidies on the Distributions of Wealth and Consumption

We have documented substantial heterogeneity in annual contributions to and withdrawals from DC accounts. In this section, we combine our data on these flows with a microsimulation model to examine the distributional impact of retirement saving subsidies on key outcomes that we do not directly observe: specifically measures of wealth at retirement. The model, which is described in full in Appendix B, simulates data on wealth and consumption in retirement by bringing together

[20]Gaps are slightly more muted in the top income bin, reflecting the fact that contribution limits bind more frequently for those in this bin.

i) our data on flows in and out of DC funds, ii) a specification of the federal tax code (from NBER TAXSIM), iii) Social Security rules and iv) assumptions about portfolio composition, asset returns, and the draw-down of wealth in retirement.

We use this model to conduct three types of exercises. First, we measure the distributional impact of the federal tax expenditure across race groups. Second, we decompose DC wealth into the shares coming from employee contributions, employer matching contributions, and federal tax expenditures. Third, we evaluate the distributional impact of changing the design of tax and employer saving subsidies.

7.1 Microsimulation model

The full model is outlined in Appendix B. Here, we summarize key inputs and outputs. The model inputs are simulated data on earnings over the lifecycle, employee and employer matching contributions to employer-sponsored DC accounts, and withdrawals from those accounts over working life. We do not observe *full* lifecycle paths (we have at most 13 years of data for any one individual), so we construct simulated data using the data that we do have and a hotdeck-based imputation procedure (described in Appendix B.2).

The key model outputs are:

- DC wealth: A_i^{DC}. This is the discounted value of after-tax withdrawals from the simulated DC account balance. We assume that savers employ a draw-down rule that keeps withdrawals constant in retirement. We further divide DC wealth into three components:
  - A_i^T is the part of DC wealth arising from its favorable tax treatment. We define this as the difference between A_i^{DC} and the discounted value of withdrawals that i would have received if she had instead saved in a taxable account.[21]
  - A_i^{EE} and A^{ER} are, respectively, the parts of DC wealth, exclusive of tax benefits (i.e., $A_i^{DC} - A_i^T$), accruing from *employee* and *employer* contributions and withdrawals.
  - We will often present wealth measures as a multiple of simple average annual earnings computed over the worker's life cycle.

[21] As a plausibility check of our model, we compare our estimates of aggregate tax expenditure to DC savings with official Treasury Department figures. In 2023, the Treasury estimated the net value of tax liability foregone because of DC treatment to be \$119 billion in 2021 (see US Department of the Treasury (2023)). When we estimate a comparable figure for the US population using our simulations, we obtain \$117b. See Appendix B.8.1 for more details.

- Consumption in retirement: We define a broad measure of wealth—denoted as Consumption (C_i)—as the sum of DC wealth (A_i^{DC}) and the discounted value of Social Security payments.
- We will group individuals by the discounted value of the sum of their earnings and deferred compensation—we refer to this as lifetime earnings (LE_i). When showing results by lifetime earnings, we divide the population into 6 groups: the bottom four quintiles and the top two deciles. We split the top quintile as IRS contribution limits generate differences in saving between the top two deciles. We will also use this quantity in our counterfactual experiments, this will be our basis for redistributing the federal tax expenditure.

Figure 9 illustrates the key model outputs. Panel 9A shows average earnings by race over the lifecycle. Panel 9B shows patterns of DC wealth at retirement by race and lifetime earnings. DC wealth is expressed as a proportion of average annual lifetime earnings. For all lifetime earnings groups except the top decile, DC wealth is highest for White workers and lowest for Black workers, and intermediate to these for Hispanic workers. Due to the differences in both contributions and in early withdrawals that we have documented,[22] the Black–White gap amounts to approximately 100%–150% of average annual earnings, while the Hispanic–White gap is approximately half that. Panel 9C shows selected percentiles of wealth for each race and income group, and highlights that there is substantial heterogeneity *within* income and race groups. Panel 9D shows a similar figure for Social Security wealth (measured as the discounted value of the stream of entitlements). Given that Social Security benefits are largely determined by earnings history,[23] there are no differences by race conditional on income.

7.2 Quantifying the distributional impact of the DC federal tax expenditure

Figure 1B illustrated racial gaps in the receipt of each of earnings, employer matches, and the tax expenditure. Those last estimates were calculated using the model described here, and Figure 10 provides a more granular analysis. It shows, for every dollar of the tax subsidy received by White workers on average, the average that is received by Black and Hispanic workers. The figure shows results by lifetime earnings group, and the two panels differ by how they define the groups. In Figure 10A earnings groups are defined based on the race-specific distributions (and so the bottom group for Black workers, for example, corresponds to the poorest 20% of Black workers). In Figure

[22] Appendix Figure C.22 shows the future value of early withdrawals at retirement by race and lifetime earnings.

[23] In our model, they are completely determined—rather than largely determined, as in reality—by earnings history, as we abstract from heterogeneity in claiming age and family benefits.

10B, on the other hand, groups are defined based on the distribution of lifetime earnings in the whole population (and so the bottom group for Black workers corresponds to Black workers in the poorest 20% of the population).[24] For every dollar of the tax expenditure received the poorest 20% of White workers, approximately 30 (60) cents is received by the poorest 20% of Black (Hispanic) workers. Holding earnings constant by defining groups at the population level, gaps are smaller but remain large—for example, for every dollar received by White workers in the bottom population quintile, 61 cents is received by Black workers and 77 cents is received by Hispanic workers.

7.3 Quantifying the contribution of employer matches and tax expenditures to wealth at retirement

Figure 11 shows the contribution of employer matches and the tax expenditure to retirement wealth along the race-specific earnings distribution (panel A) and the overall population earnings distributions (panel B). High-earners save more (Dynan et al., 2004), and so saving subsidies favor them. In the bottom quintile of lifetime earnings, cummulative tax and employer subsidies are worth less than 70% of (annual) lifetime earnings. By comparison, these saving subsidies are worth more than 250% of (annual) lifetime earnings for individuals in the top decile of earnings.

Differences are also large across racial groups, even within the same earnings bin. White workers in the middle quintile of population earnings accrue a combined subsidy from employers and the government worth 161% of their average annual earnings, compared to 119% for Black workers and 148% for Hispanic workers. Differences by position in the race-specific lifetime earnings distribution are even starker: for the middle quintile of White workers, the total subsidy is worth 171% of lifetime earnings; for Black workers, it is 85%, and for Hispanic workers, it is 134%.[25]

Figure 12 shows a similar decomposition of DC subsidies, in this case splitting by parental income rather than race.[26] In both panels, each successive set of five bars represents a group based on an individual's lifetime earnings. Within each group, the individual bars correspond to quintiles of parental income. In Figure 12A, income groups are formed within parental income groups; in 12B, they are population groups. Within each own-income group, those with richer parents receive more in savings subsidies. That is, because the children of the rich save more, even conditional on

[24] The population in this case is composed only of White, Black and Hispanic workers.

[25] Appendix Figure C.24 complements this figure by (in panel A) adding DC wealth arising from employee saving, and (in panel B), showing the *shares* of DC wealth arising from employee, employer and government contributions. Shares differ somewhat by income: at the bottom of the income distribution shares coming from employee contributions, employer contributions and tax expenditures are respectively approximately 60%, 25% and 15%, while at the top they are 50%, 25% and 25%. Shares from each component by race conditional on income, are very similar.

[26] Figure C.23 in Appendix C.3 shows a comparable analysis, splitting by own earnings and education.

their own earnings (as shown in Figure 6), subsidies for savers advantage them. The differences across groups are substantial: among those in the middle population lifetime earnings quintile, the subsidies range from 140% of average annual earnings for those with parents in poorest income decile to 168% for those with parents in the richest group.

7.4 The lifetime effect of alternative retirement saving policies

In this section, we use the microsimulation model to evaluate a budget-neutral counterfactual exercise that would break the link between private saving and the amount of employer matching benefits and tax subsidies that individuals receive. In Appendix C.3, we present results from two additional counterfactuals to assess the separate effect of changing the tax treatment of retirement contributions and the design of employer contributions.

7.4.1 Description of the counterfactual policy exercise.

The counterfactual exercise changes the design of both employer and tax subsidies for retirement. A full description of the exercise is given in Appendixes B.9, B.10, and B.11, here we provide a summary.

Employer contributions. We first redistribute the employer matching contributions within each firm. That is, we calculate the aggregate employer matching contribution made by each employer, and we divide these contributions such that every employee in that firm receives the same employer contribution as a percentage of salary regardless of how much the employee chooses to contribute to the plan.[27]

Tax expenditures. Next, we calculate the aggregate tax expenditure on DC retirement savings under the existing regime (which includes the tax advantage from deferring the taxation of contributions, tax-free growth of assets, and tax penalties on early withdrawals). Then, we redistribute this tax expenditure such that that every individual receives a direct government contribution to their retirement account calculated as a proportion of lifetime earnings. This proportion is uniform across individuals and keeps the aggregate tax expenditure constant.

Behavioral responses. In our baseline exercise, we assume that individual saving rates (and therefore the individual component of DC wealth and retirement consumption) are unchanged

[27] While employer-matching contribution formulas are chosen by employers, the government can encourage employers to adopt specific contribution formulas. Arnoud et al. (2021) estimates that a majority of employees are covered by plans with a safe-harbor matching formula. Our counterfactual can be thought of as a change in safe harbor rules that shifts all employers away from offering matching contributions and toward offering non-elective contributions.

across the different counterfactual exercises. Before showing results, we discuss this assumption.

Our counterfactual exercise removes employer matching and tax incentives. As a result, individuals may choose to consume more during their working life and save less for retirement. Whether such behavioral responses change the conclusion of our distributional analysis depends on the policy's goal. On the one hand, if there is no concern about undersaving for retirement, abstracting from these behavioral responses may not change the conclusion of the distributional analysis: groups that receive more employer and tax resources in the counterfactual exercises are better off whether they decide to allocate these new resources toward consumption in working life or toward consumption in retirement. On the other hand, in the presence of a concern about undersaving for retirement, increasing consumption during working life and reducing employee retirement contributions could change the distributional impact of the counterfactual policies. The magnitude of this effect depends on the size of the behavioral response.

There is no consensus in the literature on how much private saving responds to employer matching and tax incentives. Engen et al. (1996) and Poterba et al. (1996) review and debate the implications of the early literature on saving incentives. In a more recent contribution, Choi (2015) reviews the literature on matching and finds that it is associated with a small positive effect on participation and an ambiguous effect on average contribution rates.[28] Regarding tax incentives, a recent review by Friedman (2015) notes that "tax subsidies appear to primarily affect the allocation of savings across accounts, rather than the total amount of savings."[29]

Given the lack of consensus and overall small effects found in the empirical literature, we assume no behavioral response in private saving in the baseline specification of our counterfactual exercises. In an extension, we recalculate the results assuming that each dollar of employer matching or tax subsidies generates 10 cents of additional employee savings (which corresponds to the upper bound of the 95% confidence interval in Chetty et al. (2014)). We show those results in Figure C.28. For robustness, we also present results assuming a larger response of 20, 30 or 40 cents of additional employee savings per dollar of employer match or tax incentive.

[28] Engelhardt and Kumar (2007), using cross-sectional data, estimate that an increase in the match rate of 25 cents per dollar increases 401(k) participation rates by 5 pp, while Duflo et al. (2006), in a randomized controlled trial with a one-time saving subsidy, find that increasing the match rate from 0% to 50% increases take-up by 11 pp. However, the positive effect of matching on take-up and employee contributions may not translate into higher wealth accumulation if employees reduce their nonretirement saving or increase borrowing in response. Choukhmane and Palmer (2023) estimate that approximately two-thirds of increased employee pension contributions in the UK are financed through reduced nonretirement saving and increased credit card borrowing.

[29] Ramnath (2013) finds no statistically significant effect of the U.S. saver's tax credit on the level of retirement contributions. Similarly, Chetty et al. (2014), using administrative data from Denmark, estimate an elasticity of net saving of less than 1 cent per Danish kroner (DKr) of tax expenditure on subsidies for retirement saving.

7.4.2 The reform would reduce inequality in retirement wealth accumulation by own earnings, race, and parental income.

In this section, we discuss the results from our baseline counterfactual exercise; selected companion results for two additional counterfactuals changing, separately, the tax treatment of retirement savings and the design of matching contributions are shown in Appendix C.3.

Results by own income. We find a revenue-neutral reform that redistributes tax expenditures and employer contributions in proportion to lifetime earnings (rather than in proportion to saving) would increase consumption in retirement by 5 to 10% for individuals in the bottom half of the earnings distribution (Figure 13D). These gains would come at the expense of an approximately 5% drop in retirement consumption in the top decile of the lifetime earnings. Because the losses are concentrated among those with higher lifetime income and the gains are concentrated among those with lower lifetime income, the relative gains (in percentage of lifetime income or consumption) from this counterfactual policy are significantly larger than the relative losses.[30]

Results by race. Such a policy would also lead to a sizeable reduction in racial gaps in DC wealth. As shown in Table 5A, the reform would reduce the gap between the DC wealth of Black (Hispanic) workers and White workers by 21% (20%) for those with earnings around the median of each race-specific labor earnings distribution. Proportional changes in racial gaps are even larger when we form bins based on the population earnings distribution, reflecting the fact that our counterfactual scenarios does not address differences in average income across racial groups. As shown in Table 5B, the Black-White (Hispanic-White) retirement wealth gap drops by 34.9% (27%) for individuals with earnings around the median. Gains are also large in absolute terms, Black and Hispanic individuals in the bottom half of their race-specific earning distribution experience an increase in retirement wealth equivalent to more than one year of earnings (Figure 13A).

Results by parents' income. Figure 14 shows a similar analysis, but with groups defined based on individuals' own earnings and their parents' income.[31] The patterns of winners and losers from this reform reflect the patterns of winners and losers under the status quo that were illustrated in Figure 12. Those in the bottom population lifetime earnings bin with parents in the bottom income quintile would gain wealth at retirement worth approximately 125% of their average (annual) lifetime earnings, thereby increasing their retirement consumption by approximately 7.5%.

[30] While these reforms are designed to be revenue neutral for the government and aggregate compensation neutral for the firms, they lead to a net increase in wealth on retirement, as matching resources are transferred from older workers to younger workers, who have more time to retirement to benefit from asset returns.

[31] Appendix Figure C.25 shows a similar picture by education.

The gains (as a proportion of lifetime earnings) then fall with own earnings and, conditional on those earnings, fall with parental income. Those in the top population earnings bin with parents in the top income quintile would lose wealth at retirement worth approximately 50% of their average (annual) lifetime earnings—and their retirement consumption would fall by approximately 5%.

8 Conclusion

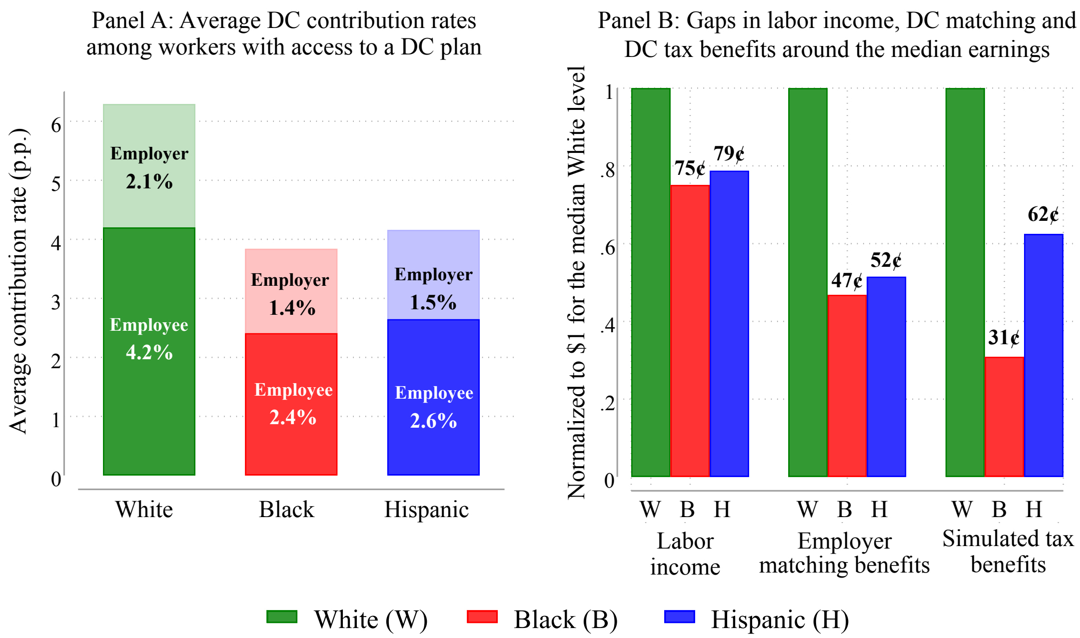
Since the introduction of the permanent income tax system in 1913, the U.S. has promoted retirement saving with tax subsidies and employer contributions. A long-standing concern is that these subsidies are regressive and largely favor higher-income individuals. This concern has sparked a long tradition of economics research studying the distributional effects and optimal design of the retirement system (Diamond, 1977; Kotlikoff et al., 1982; Geanakoplos et al., 2000; Moser and Olea de Souza e Silva, 2019). This concern is also reflected in the regulatory framework: since 1942, U.S. pension plans have been required to pass an annual nondiscrimination test to ensure that the benefits of the plan do not disproportionately accrue to highly compensated employees.[32] The income-regressive nature of retirement saving subsidies is therefore balanced by other aspects of the U.S. retirement system, which tend to be more progressive. In addition to income-based nondiscrimination tests, the Social Security formula is progressive and offers higher replacement rates for individuals with lower lifetime income.

In this paper, we examine the distributional properties of retirement saving subsidies among individuals who have similar incomes but differ along other demographic dimensions (with a focus on racial and ethnic identity). We find that the current system channels more tax and employer resources toward workers who are White, possess a college degree, and have richer parents or spouses than it channels toward their similar-income coworkers who are Black or Hispanic, are single parents, and have lower-income relatives. The consequent effects on wealth are large and are not directly addressed by other aspects of the retirement system. The Social Security formula does not vary by race, education, or parental background, and employer nondiscrimination tests consider only current compensation. Our results thus suggest that future research on the optimal design and distributional impact of retirement systems should look beyond differences along the income distribution to better understand the interplay between retirement saving policies and inequality.

[32] To pass the nondiscrimination test, the employer must show that differences between the average employee and employer contribution rates for highly compensated and non–highly compensated employees are sufficiently small. Employers can avoid these annual tests by adopting a set of plan features that qualify a plan as a safe harbor plan.

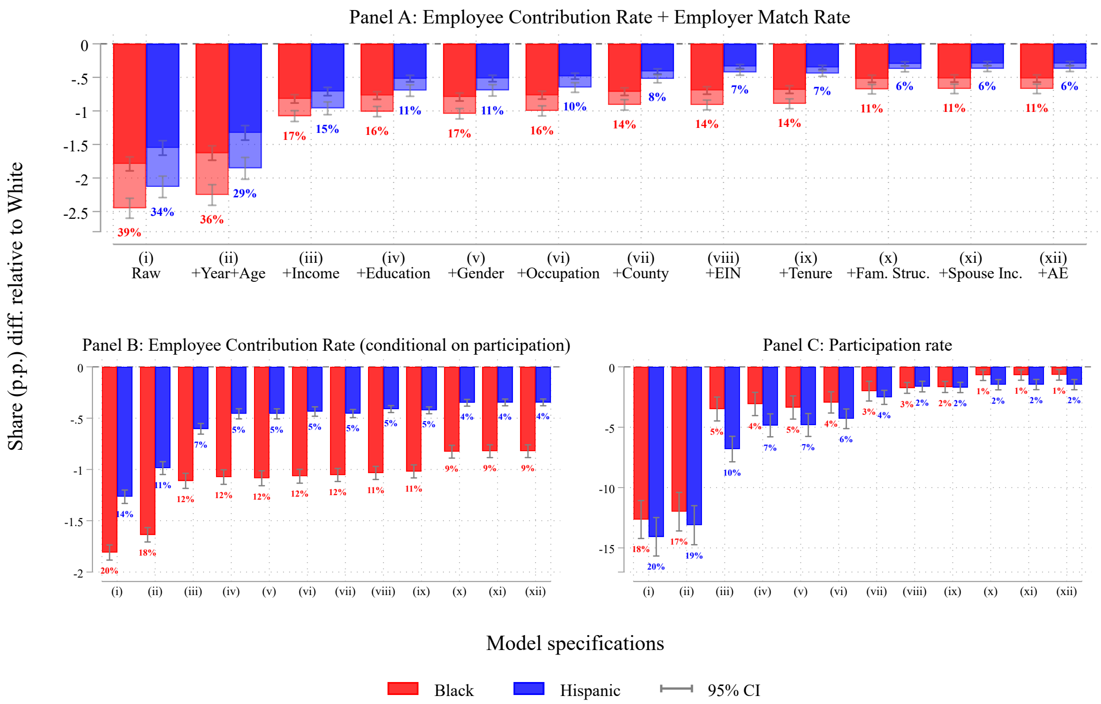
Figures

Figure 1: Racial gaps in employer matching benefits are much larger than gaps in income



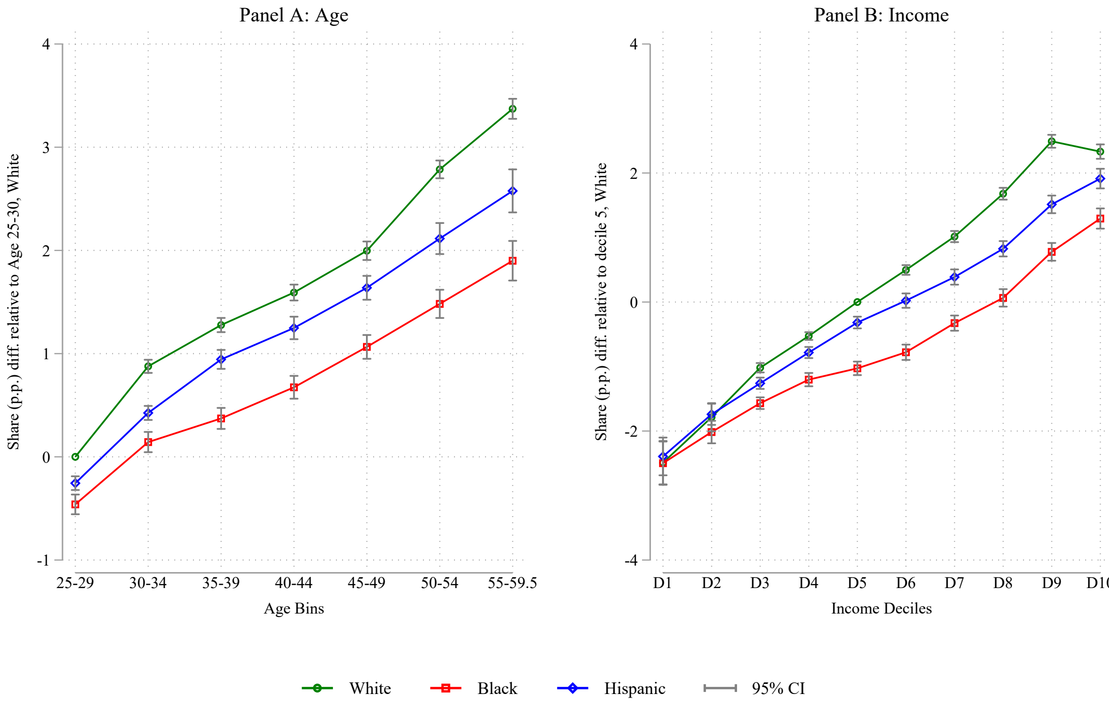
Notes: Panel A shows the average employee DC contribution rate (bottom bars) and average employer matching rate (top bars) as a proportion of salary among workers with access to an employer-sponsored DC plan and at least $8,000 in annual earnings. Panel B shows average gaps in labor income, matching contributions, and DC tax benefits for individuals around the median labor income of each group (with the White level normalized to 1). The first (second) set of three bars shows mean labor income (employer matching contributions) for those between the 45th and 55th percentiles of the race-specific labor income distribution. The third set of three bars in Panel B reports calculations from our lifecycle microsimulation model in Section 7. It shows mean model-implied tax benefits for individuals in each group between the 40th and 60th percentiles of the race-specific lifetime earnings distribution. This quantifies the present discounted value of the deferral of taxation and exemption of returns from taxation, net of tax penalties on early withdrawals.

Figure 2: Racial gap estimates for key retirement savings measures



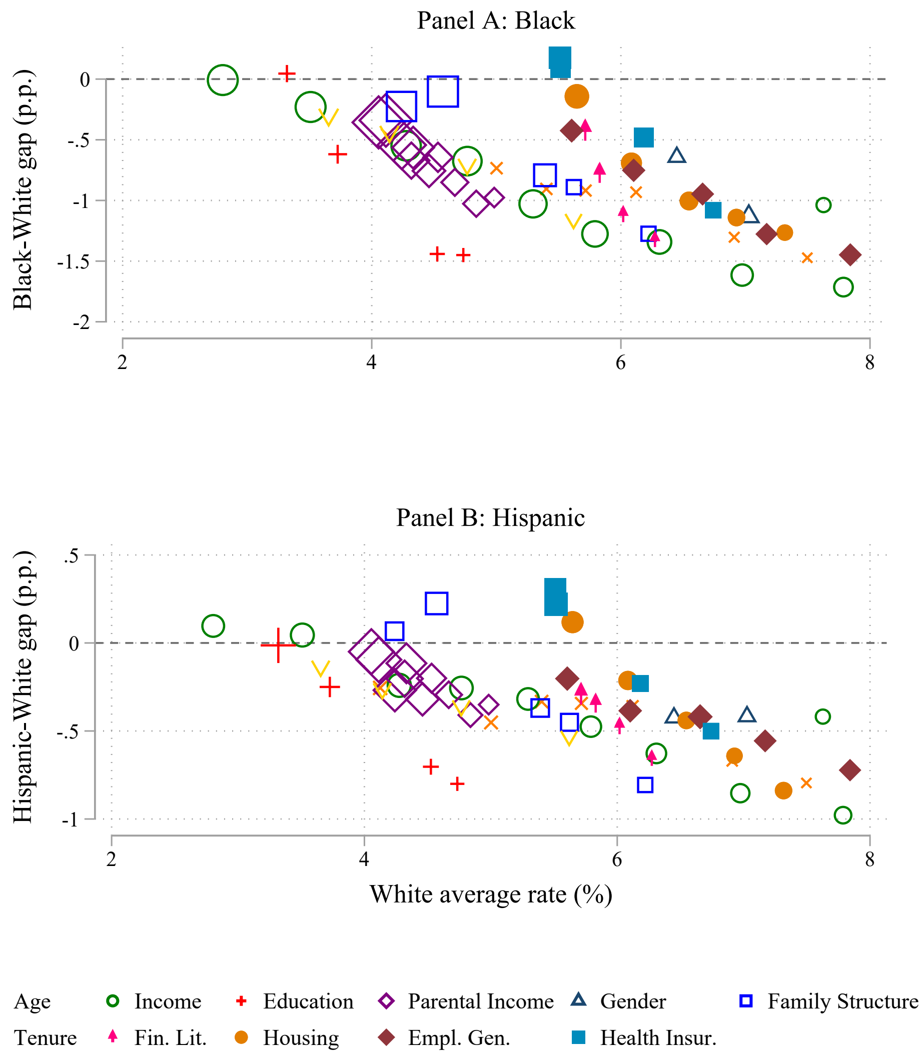
Notes: These figures give estimates on the gap between non-Hispanic White and Black or Hispanic workers, respectively, for key retirement savings measures across various model specifications. Model (i), or "Raw" as referenced in the figure, represents the univariate regression of the outcome variable on the categorical race variable: $y_{it} = \alpha + \beta_0 race_i + \epsilon_{it}$. α and ϵ_{it} are the constant and error terms, and *race* identifies, among others, the non-Hispanic White, Black, and Hispanic groups. The racial group indicators come from the ACS. In all the models, White is absorbed as the omitted category, so the coefficient on the race term, β_0, which we plot in the figures, measures the average gap between White and Black or Hispanic. Each subsequent clustered bar graph plots these Black and Hispanic coefficients from a regression model with additional mediating channels. For example, Model (ii), which is for "+ Year + Age", is $y_{it} = \alpha + \beta_0 race_i + \beta_1 year_t + \beta_2 agebin_i + \epsilon_{it}$, where $yeart$ and $agebin_i$ are vectors for year and five-year age bins, respectively. Next, we add potential mediating channels at the individual- and household- level. The potential mediating channels at the individual-level are as follows: (iii) income deciles (calculated based on the distribution of taxable wages for the given year within age bins); (iv) educational attainment bins; (v) a female dummy; (vi) occupation; (vii) county, (viii) employer fixed effects (we use the employer identification number (EIN) for each worker's main source of income), (ix) and tenure bins. Following the individual-level channels, we add household characteristics. The first household characteristic is (x) family structure (a categorical variable that records whether the individual is a single or dual filer and whether she has children). The second is (xi) spousal income, categorized into decile bins, similar to individual income, but with additional bins for those with zero income and missing spousal income (includes both single filers and those with spouses who do not submit a W-2). Finally, the fully saturated model (Model (xii) or "+ AE") comes at the end of each panel: $y_{it} = \alpha + \beta_0 race_i + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \beta_7 familystructure_i + \beta_8 spousalincomebin_i + \beta_9 AE_i + \epsilon_{it}$. Since our data set is a repeated cross-section, we calculate clustered standard errors by EIN.

Figure 3: Racial savings gaps by age and income



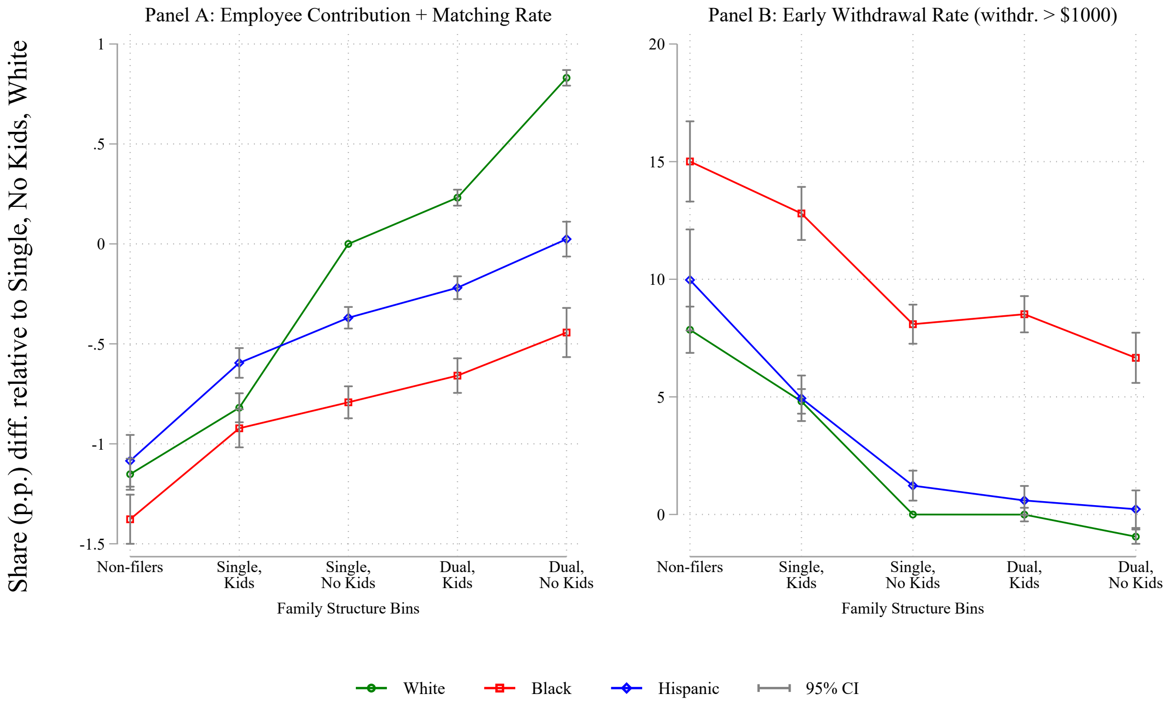
Notes: This figure illustrates racial gaps in savings for different age groups (Panel A) and income deciles (Panel B). Panel A shows coefficients on race interacted with age from a regression where the dependent variable is employee plus employer match contribution rate. The regression contains dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. For age, the regression is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(agebin_i \cdot race_i) + \epsilon_{it}$, where we graph the coefficients in ζ. The omitted dummy is for White workers Age 25-30. The coefficients in Panel B are for an analagous regression where ζ is a coefficient on income dummies interacted with race, rather than age, where the omitted category is for White workers in the fifth income decile.

Figure 4: Heterogeneity in racial savings gaps across groups relative to average savings rates of White workers in each group



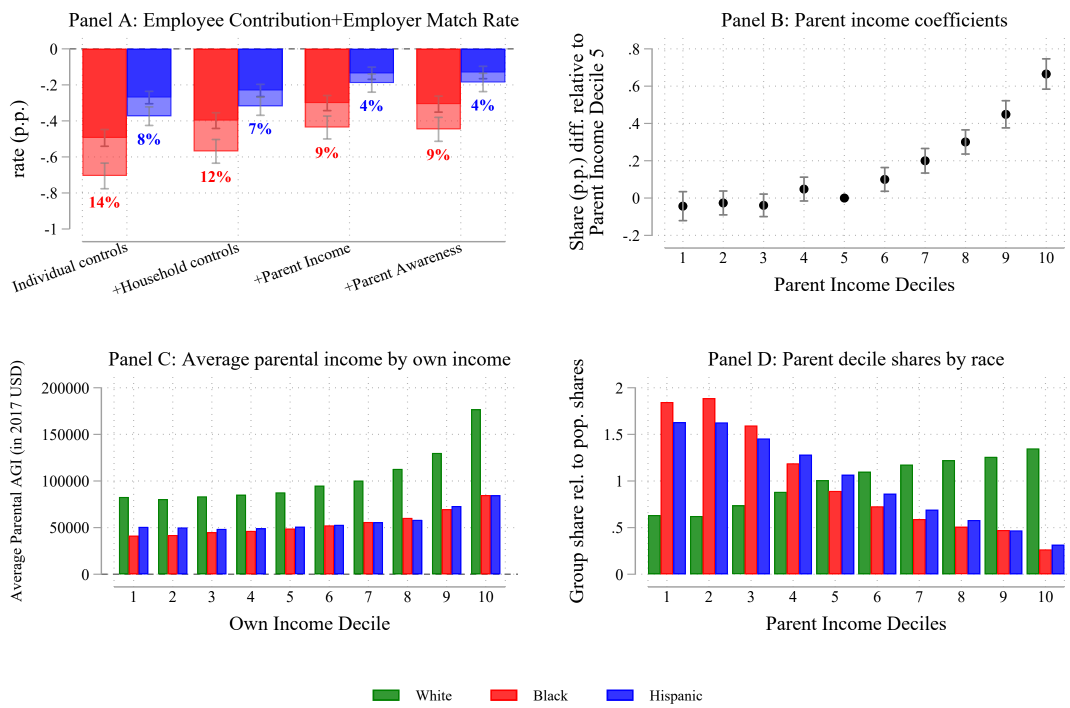
Notes: This figure shows heterogeneity in gaps in employee plus employer matching contribution rates by different mediating channels and race, relative to the corresponding White average rate. The aim is to show the broad pattern between levels of saving and gaps. Our mediating channels are age, income, education, gender, tenure, family structure, parental income, financial structure, housing costs as a share of income, financial literacy, employer generosity, and health insurance. We include dummies for year, age, education, gender, occupation, county, EIN, and tenure. The basic model for variable, var_i, is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \beta_7 var_i + \zeta(var_i \cdot race_i) + \epsilon_{it}$. We omit variables as necessary to avoid multicollinearity. For example, our financial literacy model is collinear with $\gamma_{occupation}$, so our specification is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(financial\_literacy \cdot race)_i + \epsilon_{it}$. For specific definitions and construction procedures for the listed mediating channels and other variables included in the models, please see Appendix A.1.4 and A.1.3, respectively.

Figure 5: Racial savings gaps and early withdrawals by family structure



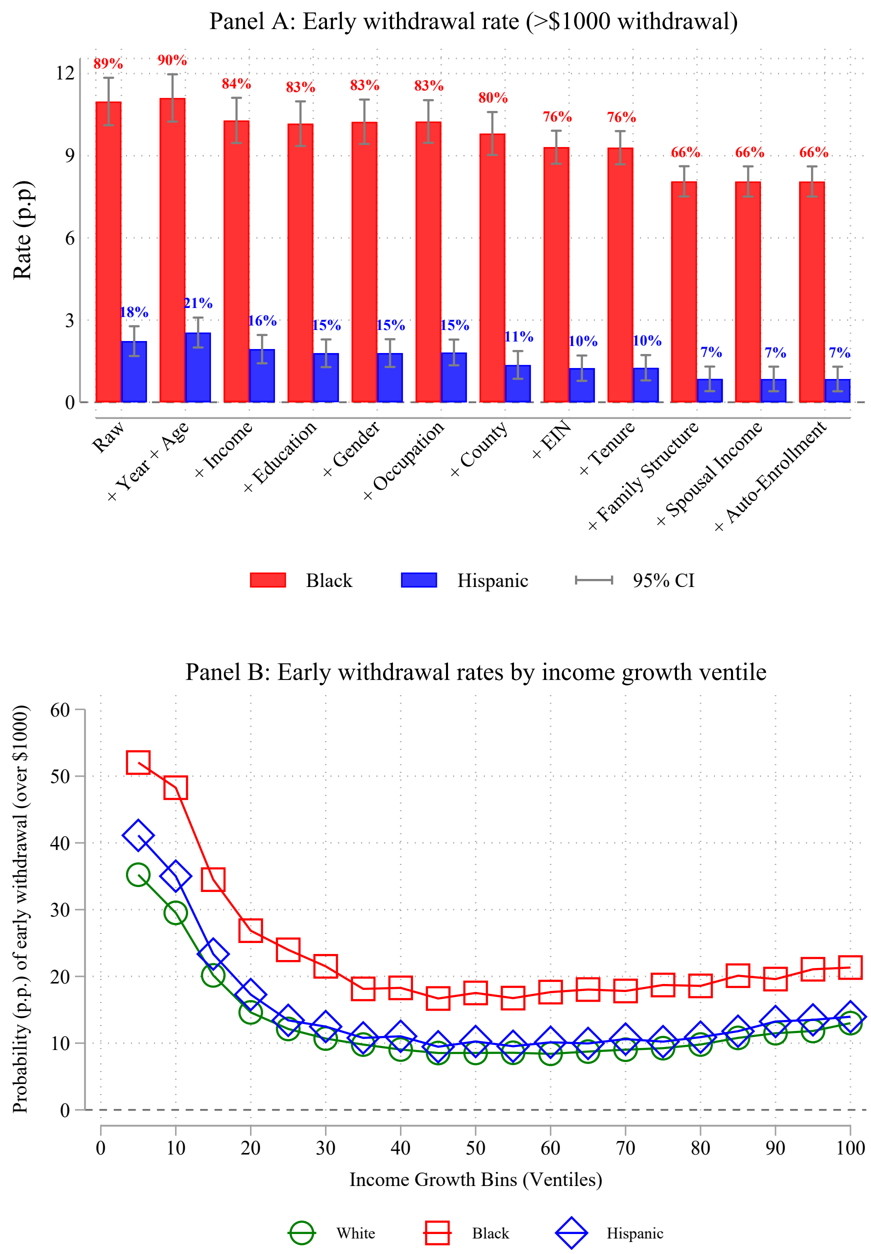
Notes: This figure illustrates racial gaps in savings (Panel A) and early withdrawals (Panel B) by family structure. The graphs show coefficients from regressions, where the dependent variables are employee plus employer matched contribution rate (Panel A), and an indicator for early withdrawal (Panel B). Regressions include dummies for year, age, education, gender, occupation, county, EIN, and tenure. The specification is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \beta_7 familystructure_i + \zeta(familystructure_i \cdot race_i) + \epsilon_{it}$. We graph the coefficients in ζ. The omitted category is White single filers with no children.

Figure 6: Racial savings gaps by parental demographics



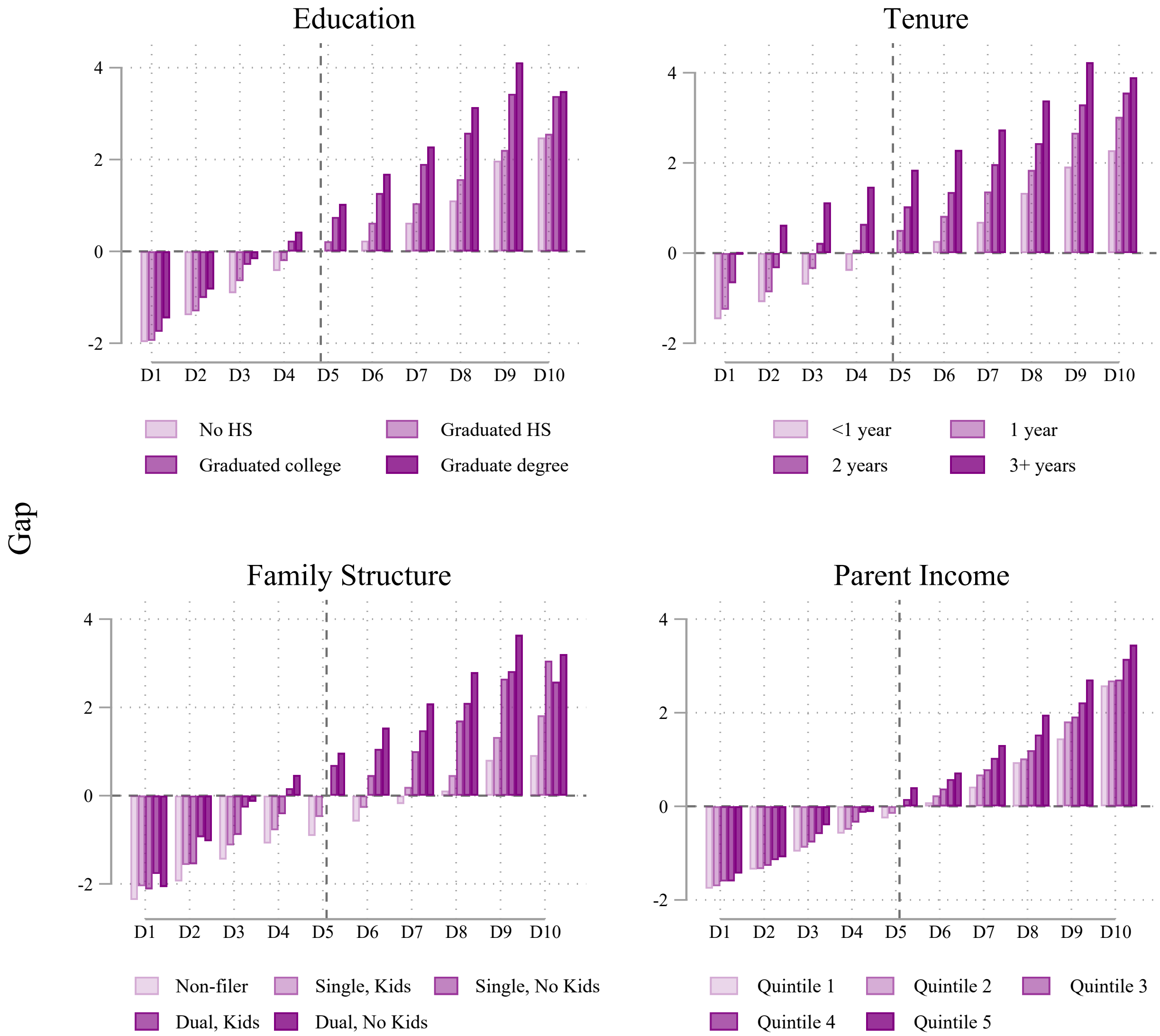
Notes: This figure illustrates the relationship between parental income and DC saving. The sample for these figures is our 'Parent Matching' sample– the sample of younger workers for whom we can link to their parents. Panel A shows estimates of the Black-White and Hispanic-White gaps in employee contribution rates and employer matches gaps in the manner of Figure 2. The first set of two bars are regression coefficients from a specification that includes the individual covariates up to specification (ix) in Figure 2. The second set of bars adds household structure and spousal income. The third set of bars adds dummies for parental income decile. The final set of bars adds an indicator for our observing parental DC contributions. Panel B gives the coefficients for each parent income decile dummy in our fully saturated model (that which is the basis for the final set of columns in Figure 6). The outcome variable is the employee contribution plus employer match rate in Panel A. Panel C shows the average parental income by population-level income bins for our observed White, Black, and Hispanic workers. Panel D illustrates the racial composition for parents within each parent income decile. For example, the height of the green bar in parental decile 1 gives the ratio of the share White workers who have parents in population income decile 1, to the the share of all workers who who have parents in population income decile 1.

Figure 7: Early withdrawals from retirement savings by race and income growth



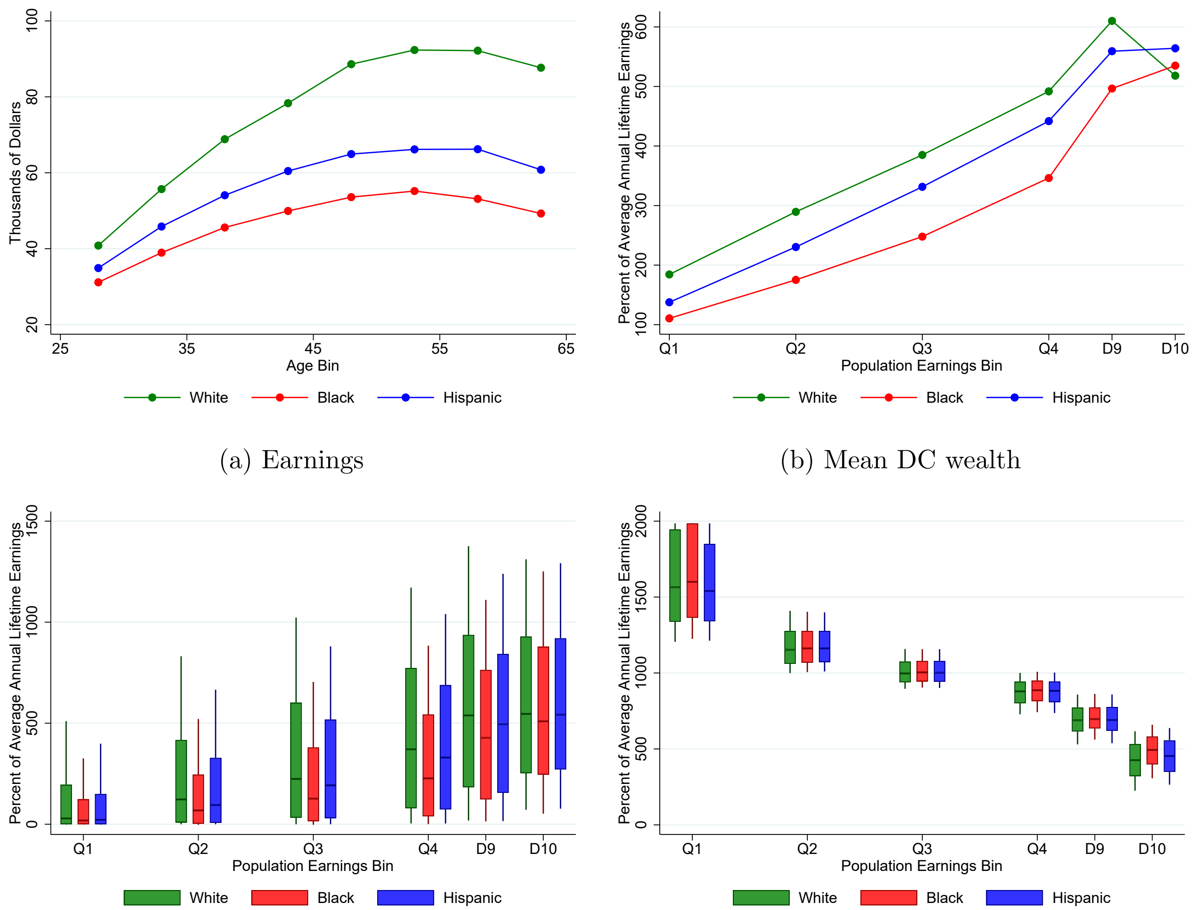
Notes: These figures show the probability of taking an early withdrawal of at least $1,000. The sample is our matching sample. Panel A follows the same structure as Figure 2A and shows the progression of the gaps for Black and Hispanic workers relative to White workers as we add potential mediating channels. We include dummies for year, age, income, education, gender, occupation, county, EIN, tenure, spousal income, and auto-enrollment. Panel B shows the breakdown, by race, in the probability of early withdrawals over $1,000 in year $t+1$ by income growth ventile from year $t-1$ to year t (where t is the year we observe individuals in the ACS). We generate early withdrawal dummies only for people who i) contributed over $1,000 in deferred compensation in the prior 4 years, ii) withdrew more than $1,000 in the year following our survey year, and iii) were younger than 55 at the time of the withdrawal. All workers in our sample were employed in the survey year. Appendix A.1.2 provides a detailed explanation of our early withdrawal dummies; Appendix A.2 provides a list of restrictions.

Figure 8: Employee plus Employer Contribution, by income interacted with demographics



Notes: This figure shows gaps in employee plus employer matched contribution rates by selected mediation channels and income decile, relative to individuals in the 5th income decile who are in our selected base category. The dashed line indicates the base category (for example, age bin 25–29 for our age covariate). Beginning from the top left, we have education, tenure, family structure, and parent income. Each group of bars corresponds to an income decile. Each individual bar represents the group of people in that income decile. The legend defines each category. Our model resembles our main specification with individual level controls and but additionally includes an interaction between income and our mediating channel under study. We include dummies for year, age, education, gender, occupation, county, EIN, and tenure. For example, our model for family structure is as follows: $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(familystructure \cdot incomebin)_i + \epsilon_{it}$. We omit variables as necessary to avoid multicollinearity For example, for our tenure model, which is collinear with the *tenure* variable, we set: $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \zeta(tenure \cdot incomebin)_i + \epsilon_{it}$.

Figure 9: Microsimulation model: Key outputs



(a) Earnings

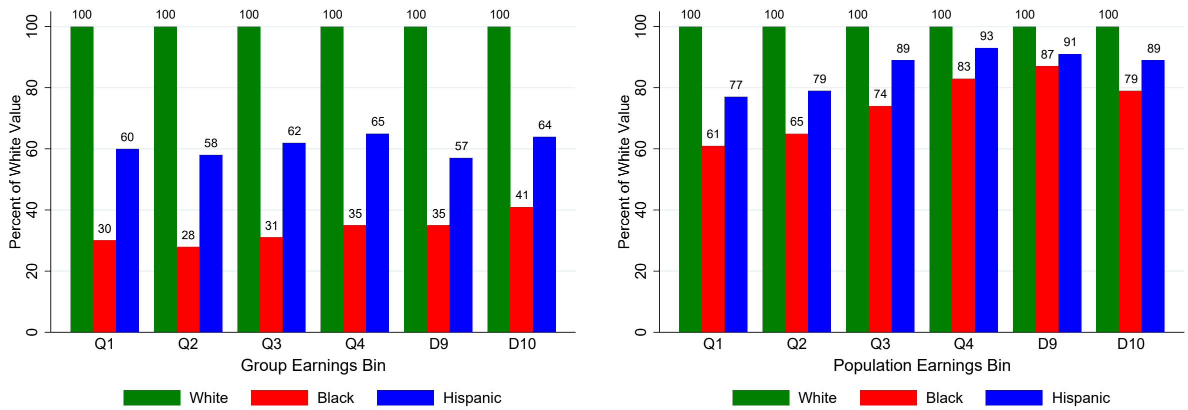
(b) Mean DC wealth

(c) DC wealth distributions

(d) Social Security distributions

Notes: This figure illustrates the features of main outputs from our microsimulation model. Panel A shows mean values by race and age bins 25–29, 30–34, . . . , 60–65. Note that the last age bin contains six ages. In Panel A, earnings are the sum of wage income and deferred compensation. Panel B shows, for each race and population earnings bin group, DC wealth at retirement divided by the simple average of earnings during working years. Lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles. Panel C illustrates the heterogeneity in DC wealth at retirement within each race and lifetime earnings group. Percentiles shown are p10, p25, p50, p75, and p90. The measure of wealth shown is the same one which was illusrated in Panel B. DC wealth at retirement divided by average lifetime earnings. Panel D shows the same percentiles for the present value of all Social Security distributions over average lifetime earnings.

Figure 10: Total tax subsidy relative to White value by race and earnings

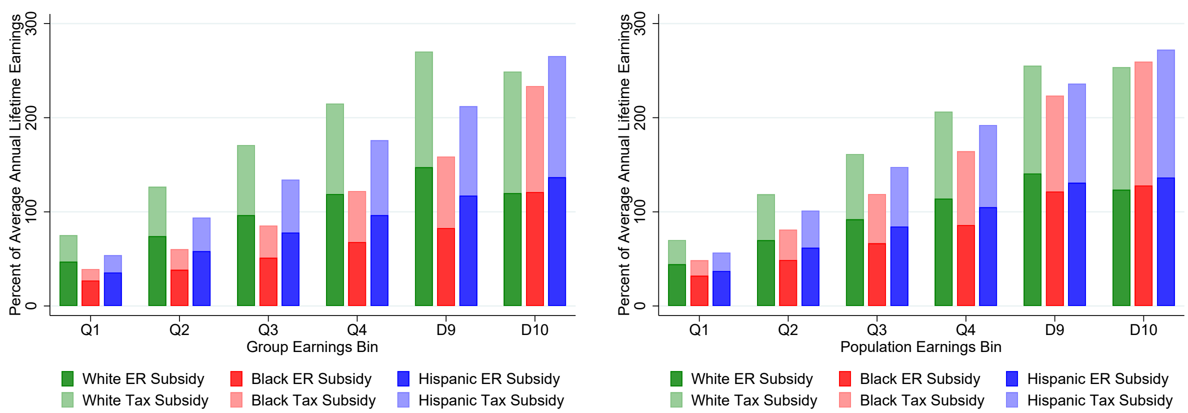


(a) By own-race quintiles

(b) By population quintiles

Notes: This figure quantifies the lifetime tax subsidy by race and earnings, expressed as a percentage of the average tax subsidy given to White savers of the same earnings group. There are six lifetime earnings group–the bottom four quintiles and the top two deciles. The figures in the two panels differ by how lifetime earnings groups are defined. In Panel A they are calculated within each race group, while in Panel B they represent population earnings groups.

Figure 11: Contributions of employer and tax subsidies to retirement wealth, by race

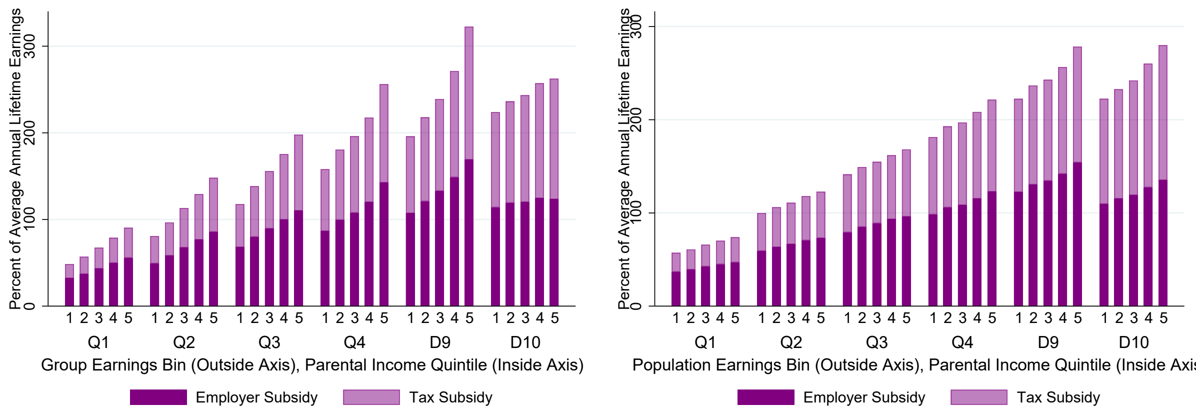


(a) By own-race quintiles

(b) By population quintiles

Notes: This figure quantifies the effect of employer matching and tax subsidies on wealth at retirement by race and earnings. The darker bars are the value at retirement of all employer matches, accounting for any preretirement withdrawals. The lighter bars are the value at retirement of the various tax advantages given to DC accounts throughout the lifecycle. Wealth levels are divided by average annual lifetime earnings to standardize comparisons across earnings levels. Lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles. The figures in the two panels differ by how lifetime earnings groups are defined. In Panel A they are calculated within each race group, while in Panel B they represent population earnings groups. Appendix Figure C.24 shows versions of the graphs by population lifetime earnings group which adds employee contributions. Panel A in the Appendix Figure shows the level of wealth and supplements Panel B in this figure, Panel B in the complementary appendix figure expresses wealth in shares and gives the proportion for each groups coming from employee contributions, employer matches, and the tax expenditure.

Figure 12: Contributions of employer and tax subsidies to retirement wealth, by parental income

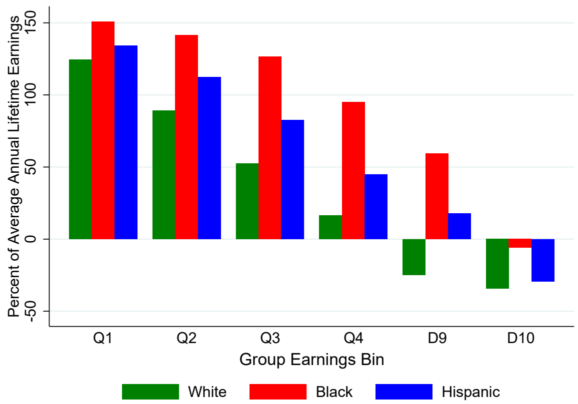


(a) By own-group quintiles

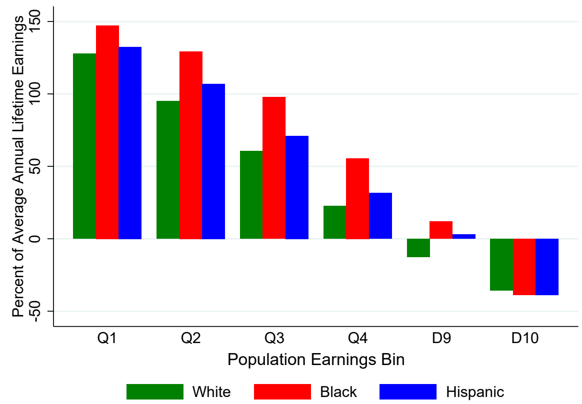
(b) By population quintiles

Notes: This figure quantifies the effect of employer matching and tax subsidies on wealth at retirement by parental income and own earnings. The darker bars are the value at retirement of all employer matches, accounting for any preretirement withdrawals. The lighter bars are the value at retirement of the various tax advantages given to DC accounts throughout the lifecycle. We divide these amounts by average annual lifetime earnings to standardize comparisons across earnings levels. Quintiles of parental income (i.e., 1, 2, 3, 4, and 5) are graphed by own-income quintile, with the top own-earnings quintile split into two deciles. Panel A has quintiles calculated within each parental-income group, while the quintiles in Panel B are calculated across parental income groups. Appendix Figure C.24 shows versions of the graphs by population lifetime earnings group which adds employee contributions. Panel C in the Appendix Figure shows the level of wealth and supplements Panel B in this figure, Panel D in the complementary appendix figure expresses wealth in shares and gives the proportion for each groups coming from employee contributions, employer matches, and the tax expenditure.

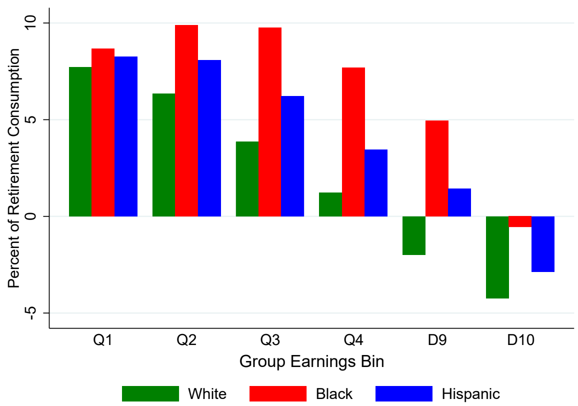
Figure 13: Change in retirement wealth and consumption, by race



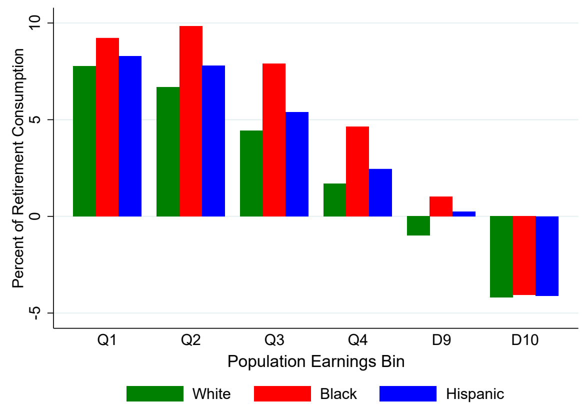
(a) Change in ret. wealth by own-race quintile



(b) Change in ret. wealth by pop. quintile



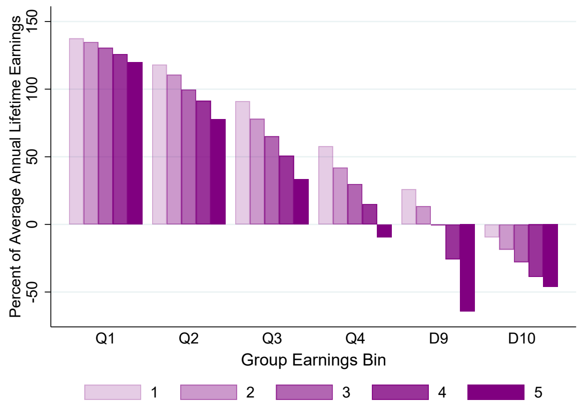
(c) Change in ret. consumption by own-race quintile



(d) Change in ret. consumption by pop. quintile

Notes: This figure illustrates the impact of our baseline counterfactual exercise on wealth on retirement and consumption in retirement. This counterfactual exercise distributes the aggregate employer matches in each firm so that all workers in that firm receive the same proportion of their earnings, and distributes the aggregate federal tax expenditure so that all workers receive a contribution that is in proportion to their lifetime earnings. We show the effect on two outcomes: the top two panels (A and B) show the change in DC wealth on retirement, with wealth expressed as a proportion of average annual working life earnings. The bottom two panels (C and D) show proportionate change in consumption in retirement (where consumption is the sum of DC wealth and Social Security). For both DC wealth and consumption, we show results by two different types of lifetime earnings bins. The graphs on the left (Panels A and C) form lifetime earnings bins within race. In the graphs on the right (Panels B and D) the bins represent population groups. In each case, lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles.

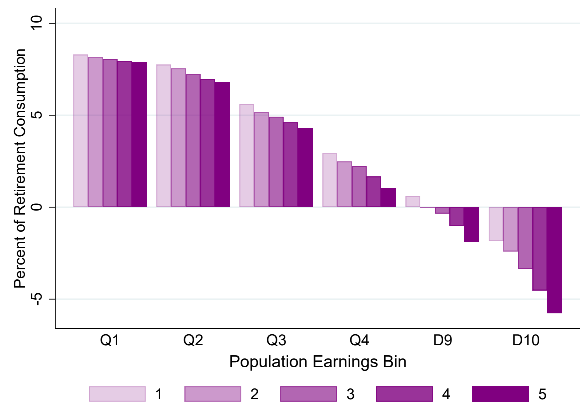
Figure 14: Change in retirement wealth and consumption, by parental income



(a) Δ wealth, by parental inc., own-group quintile

(b) Δ wealth, by parental inc., pop. quintile

(c) Δ cons., by parental inc., own-group quintile



(d) Δ cons., by parental inc., pop. quintile

Notes: This figure illustrates the impact of our baseline counterfactual exercise on wealth on retirement and consumption in retirement. This counterfactual exercise distributes the aggregate employer matches in each firm so that all workers in that firm receive the same proportion of their earnings, and distributes the aggregate federal tax expenditure so that all workers receive a contribution that is in proportion to their lifetime earnings. We show the effect on two outcomes: the top two panels (A and B) show the change in DC wealth on retirement, with wealth expressed as a proportion of average annual working life earnings. The bottom two panels (C and D) show proportionate change in consumption in retirement (where consumption is the sum of DC wealth and Social Security). For both DC wealth and consumption, we show results by two different types of lifetime earnings bins. The graphs on the left (Panels A and C) form lifetime earnings bins within parent income group. In the graphs on the right (Panels B and D) the bins represent population groups. In each case, lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles.

Tables

Table 1: Worker-level summary statistics, by respondent race

Panel A: White, not Hispanic	Mean	SD	P10	P50	P90
Average age	42.06	9.99	28	43	55
Box 1 W-2 total compensation	\$81,310	\$247,200	\$19,300	\$55,190	\$145,700
Participation dummy	68.9%	46.29%	0%	100%	100%
Avg employer match (\$)	\$1,974	\$3058	\$0	\$846.80	\$5,380
Employee contribution (%) of income	4.201%	4.76%	0%	3.223%	10.11%
Avg employer match (% of income)	2.092%	2.02%	0%	1.8%	5%
1099r withdrawal dummy	12.29%	32.83%	0%	0%	100%

Panel B: Black	Mean	SD	P10	P50	P90
Average age	40.14	9.727	27	40	54
Box 1 W-2 total compensation	\$46,250	\$79,220	\$14,890	\$35,730	\$84,620
Participation dummy	56.25%	49.61%	0%	100%	100%
Avg employer match (\$)	\$856.70	\$1,603	\$0	\$125.40	\$2,490
Employee contribution (%) of income	2.411%	3.273%	0%	1.009%	6.415%
Avg employer match (% of income)	1.43%	1.785%	0%	.4522%	4%
1099r withdrawal dummy	23.27%	42.25%	0%	0%	100%

Panel C: Hispanic	Mean	SD	P10	P50	P90
Average age	39.4	9.649	27	39	53
Box 1 W-2 total compensation	\$51,150	\$121,400	\$16,310	\$37,960	\$92,410
Participation dummy	54.83%	49.77%	0%	100%	100%
Avg employer match (\$)	\$992.80	\$1,885	\$0	\$106	\$2,849
Employee contribution (%) of income	2.648%	3.635%	0%	1.009%	6.977%
Avg employer match (% of income)	1.512%	1.873%	0%	.3652%	4.035%
1099r withdrawal dummy	14.52%	35.23%	0%	0%	100%

Notes: The table reports summary statistics for our wage earnings data from the matching sample (merged employee and employer data), which covers the 2008–2017 period.

Table 2: Summary of retirement contribution amounts, by respondent race

Panel A:	Percentage of salary				Annual dollar amount			
Employee Contributions	All	White	Black	Hispanic	All	White	Black	Hispanic
All workers	3.8%	4.2%	2.41%	2.65%	$3,351	$3,882	$1,495	$1,793
By age								
age 25 to 34	2.68%	3%	1.71%	2.03%	$1,792	$2,067	$821	$1,111
age 35 to 44	3.71%	4%	2.4%	2.72%	$3,408	$3,824	$1,542	$1,963
age 45 to 54	4.51%	4.86%	2.98%	3.16%	$4,356	$4,915	$2,041	$2,343
age 55 to 59.5	5.31%	5.68%	3.45%	3.69%	$4,895	$5,464	$2,288	$2,632
By income percentile								
0 to 10	1.06%	1.22%	.73%	.79%	$138	$159	$94	$103
10 to 20	1.56%	1.75%	1.15%	1.29%	$325	$365	$237	$267
20 to 30	2.18%	2.42%	1.72%	1.74%	$608	$675	$478	$483
30 to 40	2.68%	2.92%	2.18%	2.18%	$932	$1,02	$753	$747
40 to 50	3.16%	3.45%	2.48%	2.55%	$1,326	$1,455	$1,029	$1,049
50 to 60	3.66%	3.97%	2.81%	2.92%	$1,841	$2,012	$1,395	$1,432
60 to 70	4.19%	4.47%	3.25%	3.31%	$2,534	$2,723	$1,936	$1,938
70 to 80	4.88%	5.16%	3.68%	3.76%	$3,632	$3,864	$2,697	$2,687
80 to 90	5.87%	6.07%	4.45%	4.56%	$5,734	$5,956	$4,279	$4,273
90 to 100	5.9%	5.94%	4.92%	5.02%	$10270	$10610	$7,735	$8,008

Panel B:	Percentage of salary				Annual dollar amount			
Employer Contributions	All	White	Black	Hispanic	All	White	Black	Hispanic
All workers	1.93%	2.09%	1.43%	1.51%	$1,707	$1,974	$856	$992
By age								
age 25 to 34	1.57%	1.73%	1.14%	1.29%	$1,008	$1,153	$530	$682
age 35 to 44	1.98%	2.12%	1.48%	1.58%	$1,830	$2,075	$930	$1,123
age 45 to 54	2.15%	2.29%	1.65%	1.67%	$2,157	$2,449	$1,102	$1,223
age 55 to 59.5	2.24%	2.36%	1.76%	1.76%	$2,152	$2,406	$1,123	$1,234
By income percentile								
0 to 10	0.56%	0.62%	0.45%	0.47%	$73	$81	$59	$61
10 to 20	0.9%	0.98%	0.74%	0.8%	$186	$202	$152	$165
20 to 30	1.27%	1.37%	1.09%	1.1%	$350	$379	$300	$302
30 to 40	1.53%	1.63%	1.37%	1.35%	$526	$562	$468	$459
40 to 50	1.75%	1.85%	1.55%	1.52%	$724	$772	$637	$620
50 to 60	1.92%	2.02%	1.7%	1.68%	$952	$1,01	$833	$814
60 to 70	2.11%	2.2%	1.91%	1.87%	$1,256	$1,315	$1,12	$1,071
70 to 80	2.32%	2.41%	2.05%	2.05%	$1,695	$1,77	$1,481	$1,434
80 to 90	2.67%	2.75%	2.36%	2.36%	$2,556	$2,647	$2,224	$2,156
90 to 100	2.98%	3.02%	2.73%	2.69%	$5,551	$5,809	$4,437	$4,482

Notes: The table reports summary statistics for our wage earnings data by race from the matching sample (merged employee and employer data), which covers the 2008–2017 period. Values are rounded to the closest integer.

Table 3: Racial gaps in contribution rates, regression estimates

	Matched sample with plan information								All ACS
Dependent Variable	(1) Own + match contrib. (% of inc.)	(2) Own contrib. (% of inc.)	(3) Positive contrib. dummy (%)	(4) Own contrib. (% of inc., contrib.>0)	(5) Match contrib. (% of inc.)	(6) Max match - own cont (% of inc.)	(7) Positive withdr. >$1000 dummy	(8) Avg. firm match (% of avg. inc.)	(9) DC access
Black	-.67	-.52	-.66	-.82	-.16	.15	8.06	.02	6.67
	(.04)	(.03)	(.23)	(.03)	(.01)	(.01)	(.28)	(.02)	(.15)
Hispanic	-.37	-.29	–1.47	-.35	-.08	.08	.85	-.04	1.51
	(.02)	(.02)	(.22)	(.02)	(.01)	(.01)	(.23)	(.01)	(.12)
Female	.55	.41	4.3	.3	.14	-.14	–1.33	.08	4.41
Age Dummies									
age 25–29									
age 30–34	.62	.41	5.35	.38	.21	-.21	.77	.06	2.35
age 35–39	1	.69	7.54	.68	.31	-.3	1.59	.1	2.99
age 40–44	1.3	.93	8.54	.97	.37	-.36	2.16	.11	3.19
age 45–49	1.6	1.18	9.35	1.26	.43	-.42	2.91	.13	3.16
age 50–54	2.21	1.71	9.96	1.97	.5	-.49	4.24	.14	3.29
age 55–59.5	2.64	2.11	9.95	2.53	.54	-.53		.14	3.15
Education Dummies									
No HS									
Graduated HS	.19	.14	2.09	.13	.05	-.05	1.83	.1	6.23
Graduated college	.83	.64	4.75	.69	.19	-.19	-.14	.16	7.92
Graduate degree	1.15	.94	4.84	1.01	.21	-.22	.2	.19	8.77
Family Structure									
Single, No Kids									
Dual, No Kids	-.04	-.01	-.96	.07	-.03	.03	-.35	.02	-.53
Single, Kids	-.47	-.34	–1.51	-.57	-.12	.12	4.52	-.02	–1.02
Dual, Kids	-.54	-.43	–1.97	-.47	-.11	.11	.54	.03	–1.31
Non-filer	-.83	-.57	–5.68	-.59	-.26	.26	7.39	-.03	–4.03
Tenure Dummies									
<1 year									
1 year	.47	.32	-.72	.8	.15	-.16	.07	-.02	.86
2 years	1.04	.7	2.49	1.26	.33	-.34	-.15	.05	2.52
3+ years	1.84	1.28	7.96	1.73	.56	-.56	–1.53	.19	4.69

Income percentile dummies									
perc. 0–10	–1.64	-.98	–24.36	-.14	-.66	.66	.21	-.35	–21.07
perc. 10–20	–1.19	-.73	–15.64	-.23	-.46	.46	.52	-.29	–14.6
perc. 20–30	-.71	-.45	–8.63	-.14	-.26	.26	.56	-.17	–7.71
perc. 30–40	-.36	-.24	–4.01	-.09	-.12	.12	.08	-.08	–3.41
perc. 40–50									
perc. 50–60	.36	.26	2.97	.17	.1	-.1	-.34	.07	2.98
perc. 60–70	.82	.59	5.86	.4	.23	-.22	-.94	.14	5.64
perc. 70–80	1.4	1.04	8.63	.75	.36	-.36	–1.43	.21	8.13
perc. 80–90	2.17	1.63	12.08	1.17	.54	-.53	–2.74	.32	10.97
perc. 90–100	2.01	1.34	15.3	.52	.67	-.65	–4.09	.42	14.88
Spousal income percentile dummies									
perc. 0	-.03	-.01	-.26	.01	-.02	.02	-.43	-.01	.01
perc. 0–10	-.11	-.07	-.62	-.03	-.04	.04	-.2	-.01	-.19
perc. 10–20	-.12	-.07	-.56	-.05	-.05	.05	-.43	0	-.23
perc. 20–30	-.1	-.09	-.22	-.09	-.01	.01	-.44	-.01	-.01
perc. 30–40	-.07	-.06	-.17	-.07	-.01	.02	-.36	-.01	-.07
perc. 40–50									
perc. 50–60	-.01	0	-.16	.01	-.01	.01	-.67	.01	-.03
perc. 60–70	.14	.09	.64	.08	.05	-.03	–1.68	0	.36
perc. 70–80	.1	.08	.09	.11	.02	-.01	–1.6	0	.51
perc. 80–90	.36	.31	.56	.37	.05	-.04	-.89	0	.56
perc. 90–100	.67	.61	.58	.76	.06	-.06	-.45	.02	.37
perc. Missing	-.82	-.62	–3.86	-.55	-.2	.2	.22	-.01	-.44
Auto-enrollment	.21	.03	8.28	-.19	.18	-.12	.9	.5	
Fixed Effects									
Year	x	x	x	x	x	x	x	x	x
Occupation	x	x	x	x	x	x	x	x	x
County	x	x	x	x	x	x	x	x	x
EIN	x	x	x	x	x	x	x		

Notes: This table gives regression coefficients on race dummies (relative to White) forvarious measures. Regressions are of the form specified at the end of the notes to Fig. 2. The dependent variable (y_{it}) in column (1) is the sum of own and match contributions, as a proportion of salary. In (2) y_{it} is own contribution rate. Column (3) studies extensive margin participation and y_{it} is a dummy for plan participation. Column (4) studies the intensive margin: y_{it} is own contribution rate in a sample only of those participating. In column (5) y_{it} is the employer match contribution, as a proportion of salary. Column (6) investigates 'money left on the table'–y_{it} is the difference between the maximum match possible and match actually received, expressed as a proportion of salary. In column (7) y_{it} is an indicator for taking a withdrawal of more than \$1,000. The sample is those who have contributed at least \$1,000 in the previous four years. Column (8) and (9) are firm level analyses. Column (8) studies plan generosity–y_{it} is the maximum match that employees can receive. In column (9), y_{it} is an indicator for whether the firm offers a DC plan. This is observed in the administrative data and so this analysis can be performed on the full ACS sample. We include indicators for fixed effects. Standard errors clustered by EIN are in parentheses. They are suppressed on controls for brevity.

Table 4: Distribution of DC wealth at retirement by source and by race - Baseline model

Panel A: Quintiles (Q) & deciles (D) of the **race-specific** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Wealth from **employee** contributions	White ($'000)	18.5	52.3	98.9	185.8	349.7	529.2
	Black ($'000)	5.5	14.9	27.5	51.1	95	262.3
	Hispanic ($'000)	10.9	29.8	57.4	107.8	201.8	413.6
	B-W Gap	70%	71.5%	72.2%	72.5%	72.8%	50.4%
	H-W Gap	40.9%	43%	41.9%	42%	42.3%	21.8%
Wealth from **employer** contributions	White ($'000)	7.2	21.5	40.5	73.7	140.1	251.6
	Black ($'000)	2.9	7.5	14.3	26.4	44.8	119.5
	Hispanic ($'000)	5	14.3	26.9	46.9	81.9	184.9
	B-W Gap	59.6%	64.9%	64.7%	64.2%	68%	52.5%
	H-W Gap	30.6%	33.7%	33.6%	36.4%	41.6%	26.5%
Wealth from **tax** subsidies	White ($'000)	4.3	15.2	31.3	59.7	116.9	271.2
	Black ($'000)	1.3	4.3	9.6	21	41.2	111.2
	Hispanic ($'000)	2.6	8.8	19.4	38.7	66.3	174.1
	B-W Gap	69.8%	71.5%	69.2%	64.7%	64.8%	59%
	H-W Gap	40.4%	42.4%	38.1%	35.2%	43.3%	35.8%

Panel B: Quintiles (Q) & deciles (D) of the **population** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Wealth from **employee** contributions	White ($'000)	16.4	46	87.2	162.8	306.2	512.1
	Black ($'000)	8.6	24.9	49.2	101.2	229.8	416.3
	Hispanic ($'000)	11.9	34	70.4	140.4	276.8	482
	B-W Gap	47.7%	46%	43.6%	37.8%	25%	18.7%
	H-W Gap	27.7%	26%	19.3%	13.8%	9.6%	5.9%
Wealth from **employer** contributions	White ($'000)	6.4	18.8	35.8	65	121.4	238.9
	Black ($'000)	4.4	12.9	25.4	47.8	102.3	193.4
	Hispanic ($'000)	5.5	16.3	32.3	59	112	225.3
	B-W Gap	30.5%	31.4%	29.3%	26.5%	15.7%	19%
	H-W Gap	14.4%	13.5%	9.8%	9.3%	7.7%	5.7%
Wealth from **tax** subsidies	White ($'000)	3.7	13.1	27.1	52.7	98.6	252
	Black ($'000)	2.3	8.5	20	43.5	85.6	198.6
	Hispanic ($'000)	2.9	10.4	24.2	49.1	90.2	224
	B-W Gap	39.4%	35.1%	26.2%	17.4%	13.2%	21.2%
	H-W Gap	23%	20.6%	10.6%	6.8%	8.5%	11.1%

Notes: This table shows simulated wealth at retirement flowing from each of employee contributions, employer contributions, and the tax subsidies. For each component of wealth, we show means within lifetime earnings bins by race. Also shown are the gaps between Black/Hispanic mean values with the corresponding White mean. The two panels differ by how we form the lifetime earnings bins. In Panel A, we form lifetime earnings bins within race. In Pane B, the bins represent population groups. In each case, lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles.

Table 5: Change in DC wealth at retirement under the counterfactual tax and employer contribution policy

Panel A: Quintiles (Q) & deciles (D) of the **race-specific** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Absolute change in DC Wealth ($'000)	White	+19.1	+25.9	+22.1	+10.1	-23.7	-72.2
	Black	+16.3	+27.9	+35.4	+37	+32.1	-5.9
	Hispanic	+18.9	+27.5	+28.5	+21.9	+12.5	-39.8
Relative change in the racial DC wealth gap	B-W Gap	-30.3%	-25.1%	-21.4%	-14.9%	-9.6%	-5.4%
	H-W Gap	-37.6%	-26.1%	-19.9%	-12.2%	-10.6%	-5.1%
Relative change in the racial consumption gap	B-W Gap	-2.8%	-7.5%	-9.9%	-9.1%	-8.5%	-6.5%
	H-W Gap	-5.9%	-8.3%	-9.1%	-7.5%	-9.7%	-6.3%

Panel B: Quintiles (Q) & deciles (D) of the **population** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Absolute change in DC Wealth ($'000)	White	+18.4	+25.6	+23.6	+12.9	-10.8	-69.1
	Black	+20.3	+34.1	+37.3	+30.9	+10.1	-58.5
	Hispanic	+19.5	+28.2	+27.2	+17.8	+2.6	-64.3
Relative change in the racial DC wealth gap	B-W Gap	-51.2%	-45.1%	-34.9%	-24%	-17.6%	1.6%
	H-W Gap	-50.9%	-36.1%	-27%	-19%	-26.9%	.2%
Relative change in the racial consumption gap	B-W Gap	-18.3%	-28.9%	-25.9%	-20.7%	-18.2%	-0.9%
	H-W Gap	-62.4%	-17.9%	-16.8%	-15.5%	-26.6%	-2.0%

Notes: This table illustrates the impact of our baseline counterfactual exercise on wealth on retirement and consumption in retirement. This counterfactual exercise distributes the aggregate employer matches in each firm so that all workers in that firm receive the same proportion of their earnings, and distributes the aggregate federal tax expenditure so that all workers receive a contribution that is in proportion to their lifetime earnings. For each race, and for different earnings bind, the table shows the absolute change in DC wealth induced by the reform. Also shown are proportionate change in the Black-White and Hispanic-White wealth gaps. The two panels differ by how we form the lifetime earnings bins. In Panel A, we form lifetime earnings bins within race. In Panel B, the bins represent population groups. In each case, lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles.

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A Variable and Sample Construction

A.1 Variables of interest

A.1.1 Data sources: ACS demographics, W-2, 1040, and 1099-R filings

We use Form W-2 data from 2005-2020 to measure earnings and deferred compensation. The W-2 extracts available at the Census Bureau have information from Box 1 on taxable wages, tips, and other compensation. Additionally, the W-2 extracts have a summary measure of deferred compensation from Box 12 that primarily consists of employee tax-deferred contributions to DC retirement plans. Specifically, the IRS provides a deferred compensation variable that sums the Box 12 values in codes D-H, but not the individual values by Box 12 code. These codes include elective deferrals to plans under Box 12 codes D: 401(k), E: 403(b), F: 408(k)(6), G: 457(b), and H: 501(c)(18)(D). The items in boxes E-F (403(b), 408(k), and 457(b) plans) are DC plans that primarily differ from 401(k)s in which employers can provide them (such as nonprofits and local, state, and federal governments). 501(c)(18)(D) contributions cover future payments under certain Defined Benefit (DB) plans. From 2008 to 2018, an average of 51.6 million taxpayers made an average of $255 billion of elective deferrals. The average share of those dollars by Box 12 Code are D: 76 percent, E: 12 percent, F: 0.1 percent, G: 5.6 percent, and H: 0.02 percent. These boxes cover 93.6 percent of all elective retirement contributions on W-2s over this period.[33].

Crucially, since form W-2 is filed by firms, we are able to link workers to their employers through the federal Employer Identification Number (EIN) of a worker's employer. We assign each worker to the EIN associated with the W-2 job in each tax year with the highest Box 1 earnings.

In addition, we use information from Form 1099-R filings ("Distributions From Pensions, Annuities, Retirement or Profit-Sharing Plans, IRAs, Insurance Contracts, etc."). 1099-Rs contain information on withdrawals from DC plans and payments from DB pensions. However, on the 1099-R extracts available to us, we only observe withdrawals and distributions in two categories: 1) gross distributions from employer-sponsored plans and 2) IRA withdrawals.[34]

[33] Source: IRS Statistics of Income Tax States for Individual Information Return Form W-2 Statistics, Table 7.A at `https://www.irs.gov/statistics/soi-tax-stats-individual-information-return-form-w2-statistics`, accessed 09/20/2023.

[34] The IRS also excludes distributions, such as direct rollovers, Section 1035 exchanges, and Roth conversions from the 1099-R extract we use. For more information on the 1099-Rs, including separating DB and DC plans in the data, see Bee and Mitchell (2017).

We also link individuals to 1040 tax filings, both contemporaneously (in the years we observe their earnings) and for a subset of younger workers (under 42 in 2020), to the 1040 filings of their parents when they were claimed as dependents. We include non-filers who do not receive W-2s. From the contemporaneous 1040s of tax filers, we can observe marital status (from filing status) and link individuals to their spouses through the PIK of the other filer on the tax return. We then link the spouses to their W-2s to observe their earnings as well. Section A.1.3 provides a detailed procedure.

To construct intergenerational linkages and observe parental resources (for the analysis in Section 5.1), we use the dependent information on 1040 tax returns, which is available in the years 1994, 1995, and from 1998 onwards. We create a dependent claiming history that identifies any parent(s) that claimed each individual at all observed ages up to 18. Therefore, we can link individuals with their parents, conditional on the parents filing a 1040 in which they claim them as a dependent at some point during their childhood.

We begin with the universe of individuals in the ACS who were born sometime from 1978-1992 and merge it with the universe of individuals from the dependent claiming history. We construct a panel of these individuals, in which we observe the primary and secondary (when available) filer(s) who claimed them as a dependent in a certain year. For our measure of parental income, we use the parents that claimed the child at age 16 (or the nearest available age if the child was not claimed on a tax return at 16). The birth cohorts are 1978-1992 because the lower bound allows us to see parental income approximately when the individual is 16 during the 1994-2020 window, and the higher bound ensures we observe at least one data point of the individual's earnings, since we restrict our overall sample to those between the ages of 25-59.5.

Afterwards, we merge on the earnings data for the primary and secondary (when available) filer(s) for that year. The earnings data include the Adjusted Gross Income (AGI) reported in the 1040, and wage and deferred compensation as reported in the W-2. We use AGI while the child was 16 as our measure of parental income because parents are more likely to be in the workforce then (as opposed to when the child becomes a working adult and is as old as 42). Likewise, the available W-2 records likely miss when the parents were in the workforce as they are not available prior to 2005. We treat missing income information (i.e., for nonfilers) as zero. Consequently, if information is missing for both parents, we record parental income as zero, and if we have income information for one but not the other, parental income matches the income of the one parent who files. If we have income information for both, parental income is simply the average of the two. Lastly, we sort the individuals into decile-sized bins ranked by parental income and the observed individual's birth year, which we use for the basis of our analysis.

In addition, we construct a measure for parental awareness of DC contributions. From the sample of individuals whom we can link to their parents when they are close to 16, we focus on the subset for which at least one of their parents had a W-2 filed for them at some point during the 2005-2020 period. We create a dummy variable, which is turned on for those where at least one of their parents contributed to a 401(k), i.e., had strictly positive deferred compensation, during the window.

A.1.2 Outcome Variables

All variables in dollar terms are deflated to base year 2017 using the Consumer Price Index provided by the Bureau of Labor Statistics.[35]

Employee contributions This is deferred compensation reported in Box 12 of the W-2 tax form. This amount generally corresponds to contributions to an employer-sponsored contribution plan (such as a 401(k) plan).

Employee contribution rate The employee contribution rate is the percentage of salary, using the ratio of the real employee contribution reported in Box 12 divided by the sum of the real taxable wage reported in Box 1 of the W-2 and the real employee contribution. The formula is $\frac{employee\_deferred\_compensation}{employee\_deferred\_compensation+employee\_W-2\_wages}$. We additionally refer to this variable as "Own contrib. (% of inc.)" in output above.

Participation rate A dummy equal to one if the individual makes a positive contribution to a retirement savings plan. This measures contributions on the extensive margin. We additionally refer to this variable as "Positive contribution dummy (%)" in output above.

[35] https://www.bls.gov/cpi/research-series/r-cpi-u-rs-home.htm

Employee contribution rate (conditional on positive deferred compensation) The employee contribution rate conditional on positive deferred compensation. This measures contributions on the intensive margin. We additionally refer to this variable as "Own contribution (% of income, contribution >0)" in output above.

Employee contribution plus employer matching contributions This is the sum of real employee contributions and the imputed match contribution implied by the employer matching formula collected from the employer's Form 5500 filing. If an individual works more than 1 job, we match the employer matching formula to the highest-salary job. We apply the match formula to the three highest-earning jobs separately. We then aggregate up the imputed contribution to generate the real employer match contribution. This is then added to the real employee contribution for the combined employee and employer matching contributions. The formula is $\frac{employee\_deferred\_compensation+employer\_match}{employee\_deferred\_compensation+employee\_W-2\_wages}$. We additionally refer to this variable as "Employee plus employer matching contributions", "Own plus match contribution (% of income)", or "Employee contribution + employer match (% of income)" in output above.

Foregone employer matching (as a share of income) We measure the amount of potential matching contributions as a fraction of income which are foregone by the worker by not exhausting her employer's matching contribution cap. This captures a fraction of foregone labor compensation which is not received due to failure to fully exploit employer matching incentives. The formula is $\frac{max\_employer\_match-employee\_deferred\_compensation}{employee\_deferred\_compensation+employee\_W-2\_wages}$. We additionally refer to this variable as "Max match - own contribution (% of income)" in output above.

Early withdrawals We observe DC-plan withdrawals (and payments from pension plans) in Form 1099-R filings from 1998-2020, which we treat as potential early withdrawals from DC plans. We take early withdrawals from the year after individuals appear in the ACS survey. We apply three key restrictions: 1) individuals must contribute more than \$1000 in deferred compensation in the four years prior to early withdrawal, 2) individuals must withdraw more than \$1000 to be classified as an early withdrawal, and 3) individuals must be younger than 55 *at the time of* early withdrawal. This should limit the number of false-positive early withdrawals that are not from DC plans. We apply the first and second restrictions as federal law allows employers to automatically disburse individuals with under \$1000 in deferred compensation upon separation. The third restriction relates to the tax penalty for taking an early withdrawal—individuals 55 years and older are allowed to take early withdrawals without incurring the tax penalty. We additionally refer to this variable as "Positive withdrawal dummy (withdrawal >\$1,000)" in output above.

Early withdrawal as a share of income Early withdrawal as a share of income is the real early withdrawal amounts from retirement accounts reported in tax Form 1099-R divided by the real income (the sum of real taxable wage reported in Box 1 of the W-2 and Box 12 of real deferred compensation). The formula is $\frac{early\_withdrawal\_amount}{employee\_deferred\_compensation+employee\_W-2\_wages}$, winsorized at the 1% level after calculating the share.

Employee share of contributions (individual-level) The employee share of contributions is calculated differently from the employee contribution rate. For each individual, we calculate $\frac{employee\_deferred\_compensation}{employee\_deferred\_compensation+\mathbf{employer\_match}}$. The employee contribution rate is calculated relative to total compensation; the employee share of contributions is the ratio of employee contributions relative to total (employee plus employer) contributions. This is generally referred to as "employee share of contributions."

Employer share of contributions (individual-level) The employer share of contributions is analogous to the employee share of contributions and differs from the employee match rate. The formula is $\frac{employer\_match}{employee\_deferred\_compensation+employer\_match}$. This is generally referred to as the "employer share of contributions."

Firm-level employee share of contributions The firm-level employee share of contributions differs from the employee share of contributions. Employee share of contributions are calculated at the individual level. However, the firm-level employee share of contributions is the ratio of firm-level aggregate employee match divided by the sum of firm-level aggregate employer match plus employee deferred compensation. Hence, the formula is $\frac{firm\_total\_employee\_deferred\_compensation}{firm\_total\_employee\_deferred\_compensation+firm\_total\_employer\_match}$. This is also defined as the average employee contribution as a percent of average income.

Firm-level employer share of contributions The firm-level employer share of contributions is analogous to the firm-level employee share of contributions. This is the ratio of firm-level aggregate employer deferred compensation divided by the sum of firm-level aggregate employer match plus employee deferred compensation. The formula is $\frac{firm\_total\_employer\_match}{firm\_total\_employee\_deferred\_compensation+firm\_total\_employer\_match}$. This is also defined as the average employer match as a percent of average income, as seen in Table 3.

A.1.3 Control Variables

Year The ACS provides the survey year.

Age bin We generate age from the ACS birth years and the ACS survey year. We bin people into ages 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59.5.

Income bin Income is defined as the sum of total real Box 1 wages and Box 12 deferred compensation on W-2 filings. We generate income deciles from the total compensation distribution per year and individual's age, incorporating ACS weights.

Education We generate four educational categories from the ACS education variable—whether a respondent has completed less than a high school degree, is a high school graduate, has some college, a college degree, or a graduate degree.

Gender The ACS provides gender by male and female for the 2001-2019 surveys. We generate a dummy for female.

Occupation The ACS provides several hundred occupational categories. The IPUMS 2010 crosswalk provides occupation codes that are consistent over time. We match the ACS occupation codes with the consistent IPUMS 2010 codes, matching 12,260,000 out of 12,480,000 PIKs in our full ACS sample.

County The ACS provides the county of residence.

EIN W-2 filings provide EIN. We take the EIN for the highest-earning job if an individual worked multiple jobs. Retirement plans are matched with the highest-earning EIN.

Tenure Tenure is constructed by matching all ACS individuals with their employers from 2005-2020. Our W-2 filings report employers (EIN) in order of most wages earned. We take the earliest known year for each individual-employer combination. We match the start year with the individual's first EIN (employer from whom the individual earned the highest wages) during the ACS survey year. Since our universe of W-2s begins in 2005 and our build begins in 2008, to avoid censoring issues we classify tenure at the main employer into four main categories: 1) working less than one year, 2) between 1-2 years, 3) between 2-3 years, and 4) at least 3 years.

Family structure We construct family structure from 1040 filings. The five main groups include single, no kids; single, with kids; dual, no kids; dual, with kids; and non-filers. We include non-filers as individuals may receive W-2s but either forget or choose not to file 1040s.

Spousal income Spousal income is linked using 1040 filings from the ACS observation year. Spousal income is the sum of total real Box 1 wages and Box 12 deferred compensation from W-2 filings. Spousal income bins are classified by year and age using ACS weights into 12 main indicators: i) 0 percentile (spouses who report $0 in earnings), ii) 10, 20, ..., 100 percentiles (spouses for whom we have nonzero earnings), and iii) missing (individuals who are either single, non-filers, or for whom we cannot match spousal income).

Auto-enrollment Auto-enrollment is taken from our universe of W-2 filings and matched firm data. Our Form 5500 filings report whether a 401(k) plan offers auto-enrollment in a given year. We classify Form 5500 filings that do not report an auto-enrollment start date after 2005 as not offering auto-enrollment. Individuals who start at their main firm after firms enact an auto-enrollment policy are classified as having auto-enrollment. Individuals who start at their main firm before an auto-enrollment policy begins or work at firms without auto-enrollment policies are classified as not having auto-enrollment. Due to censoring issues, individuals who are observed starting at a firm in 2005 and work at firms where auto-enrollment begins either before or during 2005 are classified as unknown.

Parental income Parental income is adjusted gross income for parents that we can link to ACS respondents in 1040 filings. They are linked closest to when a person is claimed at age 16. We generate parent income bins by year and child's birth year (as a proxy for child age) from W-2s. Note that we do not incorporate ACS weights in our calculation of parent income bins.

Parental awareness of 401(k) Parental 401(k) awareness is generated from positive deferred compensation on filed parental W-2 filings.

A.1.4 Supplemental Variables

Health insurance The ACS provides health insurance status. Health insurance is pooled into four main categories: 1) private, 2) public, 3) private and public, and 4) other or missing.

Housing share of income Housing costs as a share of household income are taken from W-2 filings and ACS reported household income. Housing costs are the sum of mortgage payments, rent, and utilities as reported in the ACS. Some of the ACS reported household incomes are negative due to debts. We sum individual and spousal income as an alternate household income. We take the maximum household income from either the W-2 universe or the ACS to calculate housing costs. Housing as a share of income is binned into quintiles by year and age and a "missing" category for any individuals to whom we cannot match housing share of income.

Financial literacy We match the U.S. Department of Labor's Occupational Information Network Project (O*NET) with the ACS occupation codes for 2001-2009 and 2000-2019 using a bridge provided by the FSU-UM Census Occupation Code-Occupational Information Network (O*NET) Data Project. We are able to match 12,260,000 individuals (98.23%) in our sample. We generate financial literacy for each occupation by averaging across mathematical, accounting, financial, and economics knowledge and skills. Average financial literacy is binned into quintiles, with a "missing" category for any observations to whom we cannot match financial literacy.

Maximum employer match Our Form 5500 hand-coded data provide the maximum percentage that employers match in contributions. Maximum employer matching is first matched with individuals, then binned by year into quintiles. This represents the maximum employer match for our sample of ACS-retirement-plan-matched employees.

Average firm match (% of average income) We calculate the average firm match (% of average income) for each firm across our individuals. We first match with individuals, then by year into quintiles. This represents the average firm match rate as a percent of average income for our sample of ACS-retirement-plan-matched employees.

A.1.5 Other Variables

Vesting status Vesting status is taken from our universe of W-2 filings and Form 5500 data. Our retirement plan data provides information on the year in which employees are fully vested. We generate indicators for being fully vested if an individual's tenure meets or exceeds the fully vested requirements.

DC Access We construct DC access from the universe of W-2 filings. We require at least 5% of employees at a firm to have deferred compensation over the years 2005-2020.

A.2 Data Construction

This section covers our employee, employer, and merged employee-employer builds in more detail.

A.2.1 Employee data from the ACS

Our individual-level build begins with all ACS respondents from 2008-2017. Using protected identification keys (PIKs), respondents are matched with the universe of 1040, W-2, and 1099-R filings from 2005-2020. The ACS provides age, education, gender, occupation, and county. 1040 and W-2 filings provide family structure, employer ID, tenure, spousal income, inter-generational linkages (parental income and parental participation in DC plans), and direct contribution access (DC access). We further match individuals with firm-level data. From our initial build, we make several restrictions. We require that i) individuals' contributions to fall within federal tax limits for deferred compensation and ii) individuals earn more than a worker working at least 20 hours per week at the federal minimum wage. To ensure all individuals are within working age, we restrict individuals to be between 25 to 59.5 years of age.

We restrict survey years from 2008-2017 due to censoring issues. While we have ACS respondents from 2001-2019, our W-2 filings begin in 2005. Two key variables, job tenure and early withdrawals, depend on having a panel of at least four years. Job tenure is categorized into < 1 year, 1 year, 2 years, and 3+ years. Early withdrawals condition on more than \$1000 in nominal deferred compensation over the four years prior to the early withdrawal. Both require W-2 Box 1 and EIN information from the three years prior to appearing in the ACS survey. Including pre-2008 individuals would select for higher income employees who can contribute more in a given year and would attenuate their tenure. We cap our observation years at 2017 due to our retirement plan-EIN crosswalk ending in 2017. This provides us with a repeated cross-sectional data set that is representative of the United States from 2008-2017.

A.2.2 Employer data and sampling

The data set that we construct in this paper leverages the fact that that all retirement plans are obligated to submit an annual regulatory form (Form 5500) to the federal government. For plans with more than 100 participants, this form must include an attachment which contains a narrative description of the retirement plan characteristics including, amongst many other details, the match schedules (if any), vesting schedules (if any) and automatic features (if any). These descriptions have been made publicly available by the Bureau of Labor, but in their original form (free-form text) they are not amenable to empirical analysis.[36] The data set that we use (described further in Arnoud et al. (2021) on which this discussion is based, and in Choukhmane et al. (2023)) was constructed from these files for the largest 6,000 defined contribution plans, with their details codified in a consistent fashion.

The plan-level data that are constructed contain details on the full matching schedule, the vesting schedule, and any automatic features (auto-enrollment or auto-escalation). These very large firms cover a large number of employees - in 2017, 37 million employees were eligible to contribute to one of these large plans and, collectively, they accounted for 55% of the population

[36] `https://www.dol.gov/agencies/ebsa/about-ebsa/our-activities/public-disclosure/foia/form-5500-datasets`.

of workers enrolled in private and non-profit sector defined contribution retirement plans. We link these forms to the Census firm infrastructure via a multi-stage, fuzzy matching procedure which incorporates information on numeric identifiers such as EIN and telephone number as well as name and address fields.

Public filings of Form 5500 plans provide information on retirement plans, including plan identification numbers, match formulas, and total number of participants. We begin with approximately 6,200 firms (92,500 unique retirement plan ID-year combinations), of varying company and retirement plan participant sizes. We use the Hansen-Hurwitz estimator for single-stage cluster sampling. We match plan identification numbers with our employer identification numbers (EIN). We are able to match around 5,000 plans and 35,500 plan-year combinations. We drop firms that have different match formulas for different employees, that change match formulas mid-year, or for whom we cannot find match formulas. Our final restriction is requiring internal consistency checks with our universe of W-2 filings. We require employer share of contributions ($\frac{avg\_employee\_deferred\_compensation}{avg\_employee\_deferred\_compensation+avg\_employer\_match}$) from Form 5500 filings to be within 15 percentage points of our estimates of employee share of contributions from the universe of W-2 filings. This final restriction leaves us with about 3,800 unique plans and 21,500 plan-year combinations. Finally, we match plans with our individual build, resulting in 3,800 unique plans and 21,000 plan-year combinations matched in our main matching sample.

To ensure a representative sample of firms in the United States, we use the Hansen-Hurwitz estimator for single-stage cluster sampling. We collapse firm participation over all years in our sample by firm plans. We then drop firms with less than 100 retirement plan participants. The unconditional chance of being in the sample is $\frac{N_{sample}}{total\_number\_of\_US\_firms}$. We resize relative to the average firm size. To account for large firms, we flag a certainty sample. We draw $N_{sample} \approx 3,800$ firms with replacement, allowing probability proportional to size. This implies the probability of being drawn may be greater than 1 for larger firms. For all samples in our certainty samples, we replace the probability with 1. Relative participant counts outside our certainty sample are rescaled to $[0, 1]$. Finally, we apply the probability weights formula, $1-(1-p)^n$ where p is the relative mean and n is the number of firms not in the certainty sample, to produce our firm probability weights.

We calculate firm probability weights before restricting on match formulas and internal consistency checks. We do this for two main reasons: 1) firms were sampled without accounting for matching formula consistency, and 2) we apply a similar procedure to the ACS individual build. This further allows us to match our firm sample with our individual sample.

A.2.3 Matched employee-employer data and sampling

We match the retirement plan build with individuals in the ACS individual-level build using federal employer identification numbers (EIN). We match retirement plans by the first listed EIN. EINs are listed in descending order of total W-2 Box 1 wages. We match on the first EIN and apply the matching rules to any supplemental jobs. Out of 12,480,000 unique individuals in the ACS individual-build, we are able to match 2,884,000 unique individuals with DC plans (accounting for all individual- and firm-build restrictions).

The ACS person weights reflect the US population. Firm weights reflect the population of firm employees for our 6000 sampled firms. However, firm weights do not cover the full ACS sample. Our analysis, which uses *individual-level observations*, needs to reflect the US population. Thus, we calculate the combined probability of a person being sampled in the ACS and in the firms.

Our matched build can be considered a two-stage clustered sample. First, we sample 6000 firms within the US, proportional to size. Then, from the representative sample of these firms, we sample the US employee population. Each individual's probability of appearing in our matched build is the joint probability of being in a sampled firm and a sampled employee. Thus, the matched individual's probability weight is the product of the ACS probability weight with the firm probability weight. Given that the ACS individual weight is a sample weight, we multiply the inverse of the ACS sample weight by the firm probability weight. This is the matched individual probability weight; the inverse is the matched individual analytic weight.

When constructing our matched build, defined as our "matching sample," we begin with separate employee and employer builds. Our analysis uses fourteen key control variables in our main regressions: race, year, age, income, education, gender, county, occupation, EIN, family structure, spousal income, auto-enrollment, parent income, and parent awareness of (participation in) a DC plan. These are listed under A.1.3. Supplemental analysis on the relationship between race with wealth and financial literacy uses health insurance, housing as a share of income (in quintiles), financial literacy (in quintiles), maximum employer match (in quintiles), and average employer match (in quintiles). These are listed under A.1.4.

The variables are generated from the employee, employer, and combined builds. Multiple variables depend on ranking individuals or firms relative to others in the employee or employer builds. This affects when we apply restrictions to the sample and what weights we use to generate ranks. Thus, we also preserve or generate the initial weights for both employee and employer builds, respectively. We calculate probability weights for our employer sample before applying our 15 percentage point restrictions on the share of employer contributions, as the weights must reflect the population of U.S. firms.

This further applies to the variables we construct. After applying earnings and age restrictions, as explained in A.2.1, we generate income deciles by year and age using the ACS sample weights. This reflects all people in the ACS who match our sample requirements. We then match the employee data with the restricted version of our employer data by their first EIN and year. After matching the employee data, we then restrict on years 2008-2017. This provides a repeated cross-section.

In parallel, we match each ACS individual with their spouse's income in the same year and generate intergenerational linkages with parents. Spousal income is defined as the sum of real Box 1 wage and deferred compensation across all the spouse's jobs. For parent income, we generate rankings for real adjusted gross income (AGI) by year by the ACS individual's birth year without incorporating weights. We merge spousal income, parent income (real AGI), and parent income deciles to the employee data using PIK. We then generate spousal income deciles by year and the ACS individual's age, using ACS weights. All income deciles are defined relative to the ACS individual's age as we observe the outcomes for the ACS individual.

Our supplemental variables that require rankings use both ACS weights and combined weights. Housing share of income is defined relative to the full ACS sample with ACS weights, by year and age, as we observe it for the full ACS sample. Financial literacy, which is modeled for each occupation and matched via occupation codes, is similarly weighted by year, using ACS weights. This is because the ranking needs to reflect the ACS sample. However, employer generosity (maximum and average employer matching) must reflect the population of both firms and individuals and be accurate. Hence, employer generosity variables are ranked using the combined weights *after* restricting for inaccuracies in match formulas.

We apply two final restrictions to compensation and control variables before running regressions.

For compensation, we require the nominal sum of Box 1 wages and deferred compensation to be greater than $8000 and require wages to be strictly greater than $0. This eliminates people who have zero wages but have deferred compensation (likely people with high wealth who are exploiting employer matches). We require control variables to be nonmissing (except for parental awareness of DC plans) to ensure consistency across all regressions. Table D.2 shows the racial and age composition for our matching sample as we restrict on nonmissing control variables.

A.3 Samples

Our analysis covers eight main samples, taken from the individual, firm, and combined firm builds. Our main samples are our matching sample, parent-matching sample, and full sample. Supplemental samples include our vesting sample and defined contribution (DC) samples. Our vesting sample is the subset of individuals from the matching sample whom we know are fully vested. Our DC sample is the subset of all ACS individuals from the full sample who have DC plan access. We construct access to DC plans from the universe of W-2s. Any firm where at least half of employees from 2005-2020 report deferred compensation is defined as providing DC plan access. We split our DC access samples into the raw DC access sample and a sample that has more than 100 employees. The restricted version of the DC access sample is comparable to our matching sample. Appendix A.4 discusses our sample's representativeness of the U.S. population.

A.3.1 Samples from the combined individual and firm builds

Matching sample This is our main sample for analysis. It contains all individuals in the ACS for whom we match Form 5500 filings that meet our match formula and internal consistency restrictions. Individuals are required to have an auto-enrollment status. This sample uses combined ACS and firm-level analytic weights. The total number of unique individuals (after dropping missing control variables) is 1,722,000.

Parent-matching sample This is our secondary sample. It contains all individuals in the matching sample that are born after 1978 and to whom we can match parent income. We require nonmissing parent income and auto-enrollment statuses. This sample uses combined ACS and firm-level analytic weights. The total number of unique individuals (after dropping missing control variables) is 447,500.

Vesting sample The vesting sample contains all individuals in the matching sample who are fully vested in their ACS year. We require auto-enrollment status. This sample uses combined ACS and firm-level analytic weights. The total number of unique individuals (after dropping missing control variables) is 1,243,000.

A.3.2 Samples from the individual build

Full sample This is the basis for all samples. It contains all individuals in the ACS. This sample uses ACS analytic weights. The total number of unique individuals (after dropping missing control variables) is 12,140,000.

Parent sample This is a supplemental sample, included for representativeness. It is the subset of individuals in the ACS who are born after 1978 and to whom we can match parent income. This sample uses ACS weights. The total number of unique individuals (after dropping missing control variables) is 3,154,000.

DC access sample This is a supplemental sample. It is the subset of individuals in the ACS who have DC access. This sample uses ACS analytic weights. The total number of unique individuals (after dropping missing control variables) is 9,595,000.

Restricted DC access sample This is a supplemental sample. It is the subset of individuals in the ACS who have DC access and more than 100 employees. This sample uses ACS analytic weights and is comparable to our matching sample. The total number of unique individuals (after dropping missing control variables) is 2,699,000.

A.3.3 Samples from the firm build

Matched Form 5500-W-2 sample This is the sample of Form 5500 firms for whom we can match employer ID numbers from our universe of W-2 filings. To ensure consistency between our collected retirement plan data and our W-2 filings, we require each firm's share of contributions to deferred compensation from the Form 5500 data to be within 15 percentage points of our W-2-imputed firm share of contributions. This ensures that our imputed employer matches are accurate and consistent. Figure C.31 shows our W-2 imputations and reported Form 5500 data have a correlation of .896 and R^2 of 0.96.

A.4 Data representativeness

This section addresses concerns with the representativeness of our results. The first concern, in relation to our retirement plan data, is whether the matching sample represents the employed population of the U.S. that has access to deferred compensation plans. The second concern, related to sample restrictions, is whether dropping individuals with missing demographics skews the racial and age compositions of our samples.

A.4.1 Representativeness across samples

We first address whether matching ACS individuals with our retirement-plan data biases our results, given that our matching sample is effectively a two-stage clustered sample. Table D.1 provides the distribution of key retirement savings outcomes. Appendix A.1.2 provides variable definitions.

The three key comparison samples are the full sample of ACS employees, the restricted DC access sample, and the matching sample that merges the full individual and retirement plan builds. All three samples show the distribution conditional on nonmissing individual and household demographics. We compare the restricted DC access sample with the full and matching samples, as the matching sample samples from the largest 6000 firms in the US; public filings are only required for firms with over 100 employees. The restricted DC access sample carries the same 100-employee restriction. We thus compare the DC access and matching sample, as the DC access sample is the subset of all ACS individuals at large firms with access to retirement plans; the matching sample is the subset of ACS individuals to whom we match large firms and retirement plans.

As Table D.1 shows, employees in our matching sample have an average real compensation of \$72,810 while employees in our restricted DC access sample have an average real wage of \$74,330. Median real compensation is respectively \$49,260 and \$51,240, while the 90th percentile of real compensation is respectively \$133,500 and \$135,600. All values are within \$2,000 of each other. Average deferred compensation is respectively \$3,351 and \$3,495. Participation rates are respectively 65.23% and 66.29%. Early withdrawal rates (conditional on > $1,000 in withdrawals) are respectively 13.5% and 12.96%. Even household demographics are similar—average real spousal income is, respectively, $9,842 and $9,931.

Since our analysis focuses on employees who have access to deferred compensation plans, we expect real compensation, real deferred compensation rates, and participation to be significantly higher than our full sample. The fact that our DC access and matching samples are so similar while displaying expected gaps relative to our full sample indicate that our matching sample is representative of the US labor force working at large firms.

A.4.2 Representativeness in racial composition

Another concern is representativeness in racial and age composition as we control for individual and household demographics. Table D.2 shows how the composition of the full individual sample, the restricted DC access sample, the main matching sample, and the parent-matching sample change by race as we restrict for individual and household demographics. The sample composition by race is similar across race and age for both the matching and parent-matching sample. Sample compositions by race are similar across race for all samples, even as we restrict for nonmissing individual and household demographics.

A.5 Patterns of heterogeneity

In this subsection, we discuss in further detail the heterogeneity results referenced in Section 4.4.

Education. Racial gaps between Black (Hispanic) workers and White workers increase with education from 0.62 p.p. (0.01 p.p.) lower contributions for high-school graduates to 1.5 p.p. (0.80 p.p.) lower contribution rates for graduate-degree holders. Please see Figure C.10.

Gender. White women contribute 0.58% more than White men with similar characteristics and, consistent with the broad pattern in Figure 4, the Black-White savings gap is larger for women (-1.1%) than for men (-0.64%). For Hispanic workers, gaps are similar across genders. Please see Figure C.11.

Tenure. White workers with three or more years of tenure save nearly 2.0 p.p. more than White workers in their first year of tenure. The Black–White (Hispanic–White) contribution gap increases from -0.34 p.p. (-0.16 p.p.) for workers in their first year of tenure to -1.2 p.p. (-0.55 p.p.) for those with at least three years of tenure. Please see Figure C.12.

Financial Literacy: We create a proxy for financial literacy using data from O*NET on the level of knowledge in mathematics, accounting, economics, and finance across occupation codes (see Appendix A.1.3 for details). Retirement contribution rates are increasing in our measure of financial literacy and so are the racial contribution gaps. The Black-White (Hispanic-White) savings gap increases from -0.69 p.p. (-0.56 p.p.) in the bottom quintile to -1.3 p.p. (-0.66 p.p.) in the top quintile of our financial literacy measure. Please see Figure C.18.

Employer Generosity. We define employer matching generosity as the maximum employer match as a percentage of salary that one could receive by fully exploiting the matching formula. Across all racial groups, contribution rates are increasing in our measure of employer generosity: for instance, White workers with an employer in the top quintile of matching generosity contribute 2.2 p.p. more than those with employers in the bottom quintile. Racial contribution gaps also grow with matching generosity, the Black–White (Hispanic–White) gap for employees increases from -0.42 p.p. (-0.20 p.p.) in the bottom quintile to -1.3 p.p. (-0.72 p.p.) in the top quintile. Please see Figure C.17.

Health Insurance. Contribution rates are uniformly low among those with no access or only public access to health insurance, while racial gaps are larger for workers covered by private health insurance: Black (Hispanic) workers with a private health care plan contribute 1.1 p.p. (0.50 p.p.) less than their White counterparts. Please see Figure C.16.

B Microsimulation Model

B.1 Overview

Our analysis is in two parts. The first confronts the fact that, to understand the implications of differential saving and match patterns over the whole lifecycle, we need full lifecycles of data on retirement plan access and DC plan withdrawals in the population. However, we have a maximum of 13 years of observations per individual. We use these partial lifecycles and a simple hot deck imputation strategy to construct panels of synthetic lifecycles, described in Section B.2.

The second is a development of a microsimulation model, described in Section B.4, which has three objectives. The first objective is to use the data on the flows that we observe (earnings; contributions to, and withdrawals from, DC accounts) and a model of the economic and policy environment to generate simulated data for objects that we do not directly observe: the stock of resources for retirement, Social Security entitlements in retirement, and the trajectory of withdrawals from retirement accounts.

The second objective is to evaluate what would be the differences in wealth at retirement if the individual saved in a taxable brokerage account rather than the tax-advantaged defined contribution account. This allows us to build a measure of the value of tax expenditure at the individual level and to measure its distributional incidence.

The third is to evaluate what would be the distributional impact of changes to retirement savings institutions in the US. We consider three counterfactual policies. In the first, we break the link between saving and remuneration by calculating the counterfactual employer contribution for each firm which, if paid to every employee in proportion to their earnings, would cost the same to the employer as their current matching contributions. We evaluate what would be the distributional impact of moving from the status quo to a system where all employees received that contribution. The second counterfactual setting that we study breaks the link between government contributions to retirement accounts and savings choices by redistributing the tax expenditure so that it is proportional to lifetime income, once again regardless of the taxpayer's retirement savings choice. The third combines both reforms.

B.2 Modeled Lifetime Paths of Earnings, Retirement Plans, and Withdrawals

In order to estimate our microsimulation model and evaluate the distribution of tax and wealth impacts of Defined Contribution (DC) retirement plans, we need to capture the distribution of paths of earnings, retirement plan access, and DC plan withdrawals in the population. However, our data is limited in several respects. First, for many workers entering now close to retirement, DC plans were not in wide use at the onset of the working career. Furthermore, Form W-2s, our data source for individual wage and salary earnings and contributions to DC plans, are only available starting in 2005. Our information on plan characteristics from the Form 5500 is only available through 2017. That leaves us with up to 13 years in the period from 2005 to 2017 to simultaneously observe earnings and DC contributions from W-2s, plan characteristics and matching from the Form 5500s, and withdrawals on Form 1099-Rs. Our aim is to convert these shorter windows of information into plausible lifetime trajectories spanning working ages from 25 to 65.

To construct the plausible lifetime trajectories, we use a simple hot deck imputation strategy. We partition ages starting at age 25 into overlapping bins of 4 years (25-28, 27-30, 29-32..., 63-66). For a given age bin b, we observe their ages at t, $t+1$, $t+2$, and $t+3$. For individuals in bin $b+1$, we observe their ages in $t+2$, $t+3$, $t+4$, and $t+5$. We use the information from individuals in bin $b+1$ to impute earnings, DC plan access, contributions, characteristics, and withdrawals to individuals in bin b. We do so by matching individuals in bin b to similar individuals in $b+1$ using the information observed at the overlapping ages ($t+2$ and $t+3$) and appending the information from the later non-overlapping age ($t+4$ and $t+5$) to bin b individuals.

As an example, suppose Person A had earnings increasing at \$1,000 a year from \$25,000 at 25 to \$28,000 at 28. This person's firm did not offer a 401(k) plan and thus the person made no contributions to or withdrawals from a plan. Now suppose Person B had earnings increasing from \$26,500 at 27 to \$1,500 a year to \$31,500 at 30, and likewise had no access to a DC plan. Persons A and B had similar earnings and plan access in the observed overlapping ages - $y_{A,27} = 27,000$ and $y_{A,28} = 28,000$ compared to $y_{B,27} = 26,500$ and $y_{B,28} = 28,000$. As these workers had similar observable characteristics in the overlapping years, we impute to person A the information from person B at ages 29 and 30 to lengthen the number of years of earnings for Person A to cover ages 25 to 30. We can then repeat this process by imputing earnings for person A at ages 31 and 32 using individuals in the next age bin covering ages 29 to 32. For a visual representation of how this would work, refer to Figure C.32. By repeating this process, we construct lifetime histories of earnings, DC plan access, and employee and employer plan contributions.

For early retirement withdrawals of working-age individuals, we do an additional imputation step to impute withdrawals relative to contributions in the prior years to better align withdrawal amounts to contributions. This helps reduce the number of cases in the model where the withdrawals exceed recent contributions substantially. However, because we do not observe returns or contributions in the distant past, there will be many cases in the data where withdrawals exceed recent contributions, even with contributions observed over a longer time horizon than we use in the imputation.

B.2.1 Imputing DC Plan Access and Matching Rules for All Firms

A necessary input into the hot deck model described in Section B.2 is information on firm matching rules and DC plan availability for all firms. However, our data set of firm matching schedules from publicly available Form 5500 filings covers a subset of firms, including the largest 4,200 firms and a random sample of smaller firms. We use this data to impute DC access and plan matching rules to all firms. First, because we are interested in simulating lifetime trajectories for workers under the current system, we restrict to the plan characteristics in the most recent year for each firm linked to the form 5500. For all firms, we summarize the distribution of deferred contributions across their workers. As an example, suppose in a given firm, 90 percent of workers have 0 deferred compensation and 10 percent contribute exactly 3 percent of their earnings to a DC plan. We summarize the share of workers in each firm that contribute in 10 bins between 0 and 10 percent of their earnings to DC plans with separate bins for 0 contribution and > 10 percent, i.e. bins of 0, (0-1) percent, [1-2) percent, [2-3) percent, etc. We use kmeans clustering to separate firms into 10 distinct groups based on the distribution of worker deferred contributions in these bins. Finally, we impute DC plan access and firm match schedules to the firms without available Form 5500 data using a hot deck matching on the worker DC contribution clusters, firm size, and average earnings for workers at a firm. This means that if two firms, A and B, have a mass of contributions at around 3 percent of earnings, they are likely to be in the same worker contribution cluster. If firm A has plan details available from Form 5500, with matching contributions of 100 percent up to 3 percent of earnings and 0 percent thereafter. Firm A would then be a likely donor of its match schedule to firm B, which does not have available Form 5500-based plan information.

B.3 Summary and Output

The result of this procedure is a simulated data set for individuals i aged from $t \in \{25, \ldots, 90\}$, where 90 is assumed to be the last age of life and in which mortality is deterministic.

Variables that we observe (with the associated notation given for objects that will feature in the treatment below) are:

- Demographic measures: age (t) and race,
- Compensation measures: earnings (e) and contributions the employee elects to make to their

employer-sponsored defined contribution account (dc^{ee}),

- Whether the individual works in a firm offering a DC plan and, if so, the match schedule ($dc_f(.)$), and
- Withdrawals from DC accounts before retirement (w).

B.4 Model Description

B.4.1 Savings Vehicles

Central to the exercise is to compare outcomes under the status quo, in which the deferred compensation we observe is paid into a tax-deferred defined contribution account, with a counterfactual setting–in which accounts with that tax treatment are not available, and those same contributions are instead paid into a (taxable) brokerage account. We will evaluate each individual's savings trajectory under two systems of taxation, indexed by $j \in \{DC,\ BK\}$. The superscript $j = DC$ indicates that the individual is saving in a tax-deferred 401(k) account, and $j = BK$ indicates that they are saving in a brokerage account. Savings in the tax-deferred (DC) account benefit from the fact that income tax is deferred until the funds are withdrawn and that investment returns accumulate free from income and capital gains taxes. Saving in the brokerage account is made out of taxed income and has returns that are subject to tax, but withdrawals are made free of income tax.

Below we refer to the 'DC saver' and the 'brokerage saver' as shorthand for the saver in a setting where DC accounts are available and not, respectively.

B.4.2 Observable: Earnings, Contributions and Withdrawals

Employees receive compensation that can be divided into earnings $e_{i,t}$ and deferred compensation $dc^{ee}_{i,t}$. Employees may also receive an employer match, which is a firm-varying function indexed by f: $dc^{er}_f(ee_{i,t})$. In the below, for notational ease, we suppress the dependence of the employer contribution on the employee contribution and denote the employer contribution made on behalf of individual i at age t as $dc^{er}_{i,t}$.

Withdrawals from retirement accounts are denoted by $w^j_{i,t}$, with j indexing the nature of the account (DC or brokerage). We observe withdrawals made by our agents up to the age of 65. These observed withdrawals in the data are withdrawals from the DC account and are recorded before the deduction of income tax.

B.4.3 Wealth

Wealth balance at beginning-of-period is given by $B_{i,t}^{j}$ and is initialized to zero at age 25. Net flows into the wealth vehicle are denoted by $f_{i,t}^{j}$:

$$f_{i,t}^{j} = dc_{i,t}^{ee} + dc_{i,t}^{er} - \tau_{i,t}^{c,j} - w_{i,t}^{j}, \tag{4}$$

where dc^{ee} and dc^{er} are, respectively, deferred compensation by the employer and the employer-match contributions. There are two deductions from these gross flows. The first ($\tau^{c,j}$) are taxes on these contributions. This object will be defined in detail below, but, in brief, note that dc^{ee} and dc^{er} are measured as gross-of-tax. For the DC saver, no income tax is owed on these and so $\tau_{i,t}^{c,DC} = 0$. For the brokerage saver, income tax must be paid before contributions are made. The second deduction is $w_{i,t}^{j}$, which are withdrawals from the account. These are observed before the age of 65; in Section X, we propose a model of withdrawals which fills these in for after the age of 65.

The law of motion for wealth balance is given by:

$$B_{i,t+1}^{j} = (B_{i,t}^{j} + f_{i,t}^{j})(1 + \rho_t) - \tau_t^{r,j}, \tag{5}$$

where ρ_t is a rate of return that depends on age (with the time-dependence due to the changing mix of assets in the portfolio), and $\tau_t^{r,j}$ represents the taxes paid on that return in that period. This will be zero for the DC saver, and we will describe it for the brokerage saver in the next subsection.

B.4.4 Investment Returns

Two comments are needed on the investment returns. The first is that they vary with age. Each age t is associated with a portfolio composition between equities, bonds, and bills, with shares given by s_t^k, s_t^b, and s_t^m. During working years, these shares are interpolated from Fidelity target date funds.[37] In retirement, we assume exclusive investment in bonds. The age profile of investment composition is shown in Figure C.33a, and the associated age profile of real rate of return is shown in Figure C.33b. Real rates of return for these asset types (ρ^k, ρ^b, and ρ^m, respectively) are taken from Jordà et al. (2019). The combination of these assumptions yields age-specific rates of return ρ_t:

$$\rho_t = \rho^k \cdot s_t^k + \rho^b \cdot s_t^b + \rho^m \cdot s_t^m. \tag{6}$$

The second comment on returns is the division of returns into unrealized capital gains, distributions taxed as long-term capital gains, and returns taxed as income (e.g. ordinary dividend income).[38] Distinguishing between the nature of the return will be important in our treatment of the taxation of the return for the brokerage saver. The share of returns represented by each of these is given respectively by χ^g, χ^k, and χ^i, which sum to 1. The dollar flows associated with each of these three types of return are given below:

$$r_{i,t}^{g,j} = \left(B_{i,t}^j + f_{i,t}^j\right) \cdot \chi^g \cdot \rho_t, \tag{7}$$

$$r_{i,t}^{k,j} = \left(B_{i,t}^j + f_{i,t}^j\right) \cdot \chi^k \cdot \rho_t, \tag{8}$$

$$r_{i,t}^{i,j} = \left(B_{i,t}^j + f_{i,t}^j\right) \cdot \chi^i \cdot \rho_t. \tag{9}$$

Accumulation and withdrawal of untaxed capital gains When individuals withdraw funds from their accounts, they will need to realize some, previously unrealized, capital gains. This will have tax implications for the brokerage saver, and it will be necessary, therefore, for us to keep track of that part of the account balance formed of unrealized capital gains. We divide the account balance $B_{i,t}^j$ into principal $B_{i,t}^{p,j}$ and (thus far untaxed) capital gains: $B_{i,t}^{g,j}$. We define the latter

[37] We used asset allocations of the Fidelity Freedom Funds ranging from retirement years 2005 to 2065 between equities, bonds, and short-term debt as of year-end 2022. Distance to retirement is thus the target date minus 2023. A one-dimensional Akima interpolator was used to calculate shares between observed age distances to retirement. Our shares may be compared to Fidelity's own description of their glide path, such as in Fidelity (2023).

[38] The second component – distributions taxed as long-term capital gains – do not represent returns which are realized for a withdrawal. Rather they are the gains, realized as mutual fund managers trade assets, which are passed on to investors. See Fidelity's description of these distribution types at `https://www.fidelity.com/learning-center/investment-products/mutual-funds/taxes`.

recursively as:

$$B^{g,j}_{i,t+1} = B^{g,j}_{i,t} + r^{g,j}_{i,t} - w^{k,j}_{i,t}, \tag{10}$$

where $B^{g,j}$ is the cash value of the stock of unrealized capital gains in the account balance, $r^{g,j}_{i,t}$ are additional untaxed gains attained in year t, and $w^{k,j}_{i,t}$ are gains actually realized when a withdrawal is made.

Whenever a withdrawal ($w^{j}_{i,t}$) is made, we assume that the withdrawal comprises untaxed capital gains $w^{k,j}_{i,t}$ and principal $w^{p,j}_{i,t}$ in proportions that equal their share of the stock of wealth. That is, the share of any withdrawal by the brokerage saver which is subject to capital gains tax is equal to the share of unrealized capital gains in wealth:

$$\frac{w^{k,j}_{i,t}}{w^{j}_{i,t}} = \frac{B^{g,j}_{i,t}}{B^{j}_{i,t}}. \tag{11}$$

B.4.5 Social Security Income

We assume all individuals stop earning when they turn 66 and that they begin claiming Social Security benefits. Central to the determination of Social Security benefits is 'Average Indexed Monthly Earnings' (*aime*) which is the average of the best 35 years of total compensation:[39]

$$aime_i = \frac{1}{35} \sum_{k \in \text{best } 35} \left\{ \frac{\min(e_{+}dc^{ee}_{i,t},\ e^{max})}{12} \right\} \tag{12}$$

Monthly Social Security benefits are equal to 90% of *aime* up to the first 'bend point' ($895 in 2018), 32% of any *aime* above the first bend point and below the second point ($5,397 in 2018) and 15% of any *aime* above the second bend point.

B.4.6 Withdrawals

We distinguish between 'early withdrawals' and 'retirement withdrawals.' The former are those taken before the age of 65, and we observe these in our data. The latter are after the age of 65, are not observed, and so must be modeled.

[39] Recall from Section X that we are assuming an environment with zero inflation and zero real wage growth, and so there is no indexation of the earnings in equation (12) where the measure of earnings that enters the calculation is capped at a value given by e^{max}.

Early withdrawals We define early withdrawals as all withdrawals before the age of 65.[40] The measure that we observe in our data (denoted by $w_{i,t}^{DC}$) is that before income taxation, which must be paid on all withdrawals from DC accounts – for the equivalent withdrawal which will be applied to the brokerage saver (denoted by $w_{i,t}^{BK}$), we calculate the after-tax quantity retained by the DC saver.

One complication arises when the early withdrawal that we see would lead to the brokerage saver having a negative balance. This occurs in only a small share of cases (14.2%). In these cases, we adjust the measure we see in our data to be the largest number that avoids the brokerage saver going negative. This adjustment reduces the withdrawal by approximately 17.6% for that share of savers.

Retirement withdrawals Individuals retire at the beginning of age 66 with balance in their account of $B_{i,66}^{j}$. They employ a consumption rule each year to determine how much to withdraw each period t. We set this rule such that consumption for the DC saver is constant each period.

In particular, the withdrawal each period is equal to:

$$w_t^j = \frac{1-\alpha}{1-\alpha^{90-t+1}} B_{i,t}^j. \tag{13}$$

where $\alpha = \frac{1}{(1+\rho^b)}$ is defined using the return on bonds ρ^b.[41] This rule keeps pre-tax withdrawals constant. We assume that individuals consume their withdrawal, net of taxes:

$$c_t^j = w_t^j - \tau_{i,t}^{w,j}, \tag{14}$$

where $\tau_{i,t}^{w,j}$ are taxes incurred by withdrawing money from account j and will be defined in the next section. Constant (pre-tax) withdrawals keep post-tax consumption constant for the DC saver (as income does not change in retirement) and close to constant for the brokerage saver (for whom small changes in average tax rates will occur as wealth is decumulated).

[40] Not all of these will be subject to an early withdrawal penalty, which only applies to some withdrawals made before the age of 59.5. We return to this when we discuss the taxation of withdrawals in Section B.6.1.

[41] This consumption rule is that which would be obtained from a cake-eating problem in which life-span is deterministic and in which the discount rate is set equal to the interest rate.

B.5 Summary

The data that we construct, together with the features outlined above, yield two parallel data sets: one representing the earnings, savings, account balance, and withdrawals of the DC saver, and one representing the same objects for the brokerage saver. We represent these by the following:

$$\left\{\{e_{i,t}, dc^{ee}_{i,t}, dc^{er}_{i,t}, B^{DC}_{i,t}, w^{DC}_{i,t}\}^{90}_{t=25}; \{c^{DC}_{i,t}\}^{90}_{t=66}\right\} \quad \left\{\{e_{i,t}, dc^{ee}_{i,t}, dc^{er}_{i,t}, B^{BK}_{i,t}, w^{BK}_{i,t}\}^{90}_{t=25}; \{c^{BK}_{i,t}\}^{90}_{t=66}\right\}$$

where the first three objects are common across the two tuples, but the balances, withdrawals and consumption profiles differ, due exclusively to the different forms of taxation the two savers face.

B.6 Taxation

The previous section concludes by noting our data and microsimulation model yield, for each individual in our data, two trajectories of wealth accumulation and decumulation – one if they save in a DC account and one if they saved the same quantities in a taxable brokerage account. The DC saver will have, due to their access to preferential taxation, higher consumption in retirement. This section shows how we measure these differences in tax treatment across the life cycle.

At the most general level, we take the flow of income, saving and return that we measure and use TAXSIM to evaluate the taxes. This allows us to construct our summary measure of wealth at retirement: which is the present discounted value of consumption facilitated by accumulated wealth at retirement. This section provides, for the interested reader, full details on how we measure that.

B.6.1 Decomposing the overall tax burden into components

We denote our modelled tax function, which distinguishes between the three forms of income that agents in our model earn, as $T(N, K, S)$. N denotes inflows taxed according to the income tax schedule (e.g., wage income during working life and 401(k) distributions in retirement); K denotes income taxed as long-term capital gains; and S denotes Social Security benefits.[42]

[42] Note that effective tax rates in retirement are usually very low (see Chen and Munnell (2020)), due in part to the favorable tax treatment of Social Security benefits, on which many households pay no tax at all (see also Joint Committee on Taxation (2019)).

We wish to decompose the total tax burden (denoted by T) into shares that can be ascribed to earnings (τ^e), contributions to retirement accounts (τ^c), investment returns (τ^r), taxes owed on Social Security benefits (τ^s), and withdrawals from retirement accounts (τ^w). Earnings, contributions, returns and withdrawals, of course, interact in a non-linear (and quite complex) manner to generate overall tax liability. This means that there is no unique decomposition such that the total tax burden T can written as the sum of these components. This section explains how we obtain one such decomposition.

We use rules for tax year 2018 according to NBER's TAXSIM 32 tool to calculate federal income tax owed by each simulated individual.[43]

Taxation of Earnings We first define taxes on earnings ($\tau_{i,t}^{e,j}$) as follows:

$$\tau_{i,t}^{e,j} = \begin{cases} T\big(e_{i,t},\ 0,\ 0\big) & \text{if } t < 66 \text{ for } j = DC, BK; \\ 0 & \text{if } t \geq 66 \text{ for } j = DC, BK. \end{cases} \tag{15}$$

This does not differ by the type of saver, and the second equality follows from our assumption of no earnings from the age of 66.

Taxation of Social Security We define the tax on Social Security as the tax that would be paid if an agent had their Social Security income and no other income as:

$$\tau_{i,t}^{ss,j} = T\big(0,\ 0,\ ss_{i,t}\big) \quad \text{if} \ \ t \geq 66 \quad \text{and } j = DC, BK, \tag{16}$$

which also does not differ by type of saver.[44]

Taxation of Contributions Our definition of taxable earnings excluded that part of earnings which was saved for retirement: an employee's choice of deferred compensation and any associated

[43] The N, K, and S income sources are fed into the *pwages*, *ltcg*, and *gssi* fields in TAXSIM, respectively. We assume that all individuals take the standard deduction and do not claim any other credits or deductions. See Feenberg and Coutts (1993) for a description of the TAXSIM model.

[44] As it happens $\tau_{i,t}^{ss,j}$ will be zero for everyone in our sample – an individual with maximum Social Security income and no other income will not face any income tax. We retain the variable for completeness and because its exclusion may obscure some features of the exposition.

employer match $dc^{ee}_{i,t} + dc^{er}_{i,t}$. For the DC saver, income which is contributed to the account is untaxed, so $\tau^{c,DC}_{i,t} = 0$. For the brokerage saver, the tax we ascribe to contributions is equal to the additional income tax the saver would have paid by taking compensation as earnings. This is given by the second line in:

$$\tau^{c,j}_{i,t} = \begin{cases} 0 & \text{for } j = DC, \\ T\left(e_{i,t} + dc^{ee}_{i,t} + dc^{er}_{i,t},\ 0,\ 0\right) - \tau^{e,BK}_{i,t} & \text{for } j = BK. \end{cases} \tag{17}$$

where the positive term in the second line gives the income tax owed from earnings that include deferred compensation and the negative term nets off that tax already ascribed to earnings, defined in equation (15).

As we assume that there are neither earnings nor contributions after retirement age, for both savers we obtain that $\tau^{c,j}_{i,t} = 0$ for all $t \geq 66$.

Taxation of withdrawals The taxation of withdrawals depends on whether they are 'early withdrawals' (those up to the age of 65) or 'retirement withdrawals' (from the age of 65). Taking the former case first, the DC saver must pay income tax and may face a tax penalty. This penalty is incurred at a rate p_t, which is equal to 10% for non-exempt withdrawals before the age of 59.5 and is equal to 0 for withdrawals after the age of 65. The first line of equation (18) gives this quantity, the positive terms are respectively the regular income tax on earnings and DC withdrawals and the tax penalty; the negative term subtracts taxes already ascribed to earnings.

The brokerage saver need not pay income tax on withdrawals but must pay capital gains taxes on gains realized to withdraw their funds ($w^{k,BK}_{i,t}$). This quantity is defined in the second line in equation (18), where the first term gives the tax liability from earnings, contributions and capital gains and the negative term subtracts taxes already ascribed to earnings and contributions.

$$\tau^{w,j}_{i,t} = \begin{cases} T\left(e_{i,t} + w^{DC}_{i,t},\ 0,\ 0\right) + p_t w^{DC}_{i,t} \mathbb{1}(t < 60) - \tau^{e,TD}_{i,t} & \text{if } j = DC \text{ and } t < 66, \\ T\left(e_{i,t} + dc^{ee}_{i,t} + dc^{er}_{i,t},\ w^{k,BK}_{i,t},\ 0\right) - \left(\tau^{e,BK}_{i,t} + \tau^{c,BK}_{i,t}\right) & \text{if } j = BK \text{ and } t < 66. \end{cases} \tag{18}$$

In retirement, the DC saver pays regular income taxes on withdrawals (see the first line of equation (19), while the brokerage saver pays capital gains taxes on that share of withdrawals which represent previously unrealized gains ($w_{i,t}^{k,BK}$). Both savers are, at this point in their lifecycle, claiming their Social Security payments, which enter as the third argument of the tax function:

$$\tau_{i,t}^{w,j} = \begin{cases} T\big(w_{i,t}^{DC},\ 0,\ ss_{i,t}\big) - \tau_{i,t}^{ss,DC} & \text{if } t \geq 66 \text{ and } j = DC, \\ T\big(0,\ w_{i,t}^{k,BK},\ ss_{i,t}\big) - \tau_{i,t}^{ss,BK} & \text{if } t \geq 66 \text{ and } j = BK. \end{cases} \tag{19}$$

Taxes on Investment Returns All returns on funds in DC accounts are untaxed. That is, there is no taxation of unrealized gains ($r_{i,t}^{g,j}$), there is no income tax on dividend income ($r_{i,t}^{i,j}$), and there is no capital gains tax for distributions ($r_{i,t}^{k,j}$). So the taxes paid by the DC saver on returns are zero.

For the brokerage saver, while the unrealized capital gains ($r_{i,t}^{g,j}$) incur no immediate tax liability, income tax is paid on dividend income ($r_{i,t}^{i,j}$), and capital gains tax is paid on realized gains. As described in Section B.4.4, the latter come in two parts – that part of the return which is distributed even in the absence of a withdrawal ($r_{i,t}^{k,j}$), and that part of the return which is realized when a withdrawals is made ($w_{i,t}^{k,j}$).

Taxes on portfolio returns for the brokerage saver are given in (20). In both lines (representing, respectively, taxes before and after retirement), the first term gives all taxes due in a particular period (on earnings, contributions, withdrawals and returns), and the second term nets off those taxes already ascribed to earnings, contributions, and withdrawals.

$$\tau_{i,t}^{r,BK} = \begin{cases} T\left(e_{i,t} + dc_{i,t}^{ee} + dc_{i,t}^{er} + r_{i,t}^{i,BK},\ r_{i,t}^{k,BK} + w_{i,t}^{k,BK},\ 0\right) \\ \quad - \left(\tau_{i,t}^{e,BK} + \tau_{i,t}^{c,BK} + \tau_{i,t}^{w,BK}\right) & \text{if } t < 66, \\ T\left(r_{i,t}^{i,BK}, r_{i,t}^{k,BK} + w_{i,t}^{k,BK},\ ss_{i,t}\right) - (\tau_{i,t}^{ss,BK} + \tau_{i,t}^{w,BK}) & \text{if } t \geq 66. \end{cases} \tag{20}$$

B.7 Lifetime Measures

B.7.1 Implied Post-Tax Interest Rate

Our model contains multiple interest rates which could be used to evaluate the present value of future flows. To do this, we define an interest rate $\hat{r}_{i,t}$ as the post-tax rate of return that the brokerage saver would pay if their deferred gains each period were realized as long-term capital gains.[45] We first define the hypothetical taxes on portfolio returns in this case as:

$$\widehat{\tau_{i,t}^{r,BK}} = \begin{cases} T\left(e_{i,t} + dc_{i,t}^{ee} + dc_{i,t}^{er} + r_{i,t}^{i,BK},\ r_{i,t}^{g,BK} + r_{i,t}^{k,BK} + w_{i,t}^{k,BK},\ 0\right) & \\ \quad - \left(\tau_{i,t}^{e,BK} + \tau_{i,t}^{c,BK} + \tau_{i,t}^{w,BK}\right) & \text{if } t < 66, \\ T\left(r_{i,t}^{i,BK}, r_{i,t}^{g,BK} + r_{i,t}^{k,BK} + w_{i,t}^{k,BK},\ ss_{i,t}\right) - (\tau_{i,t}^{ss,BK} + \tau_{i,t}^{w,BK}) & \text{if } t \geq 66. \end{cases} \tag{21}$$

where this expression is the same as that in equation (20) except for the inclusion of $r_{i,t}^{g,BK}$ each period in the second argument. The implied, post-tax interest rate is then

$$\hat{r}_{i,t} = r_t - \frac{\widehat{\tau_{i,t}^{r,BK}}}{B_{i,t}^{BK} + f_{i,t}^{BK}}. \tag{22}$$

This rate is used across all counterfactuals.

B.7.2 Wealth

We have two measures of resources in retirement: a) Wealth which just takes account of the value in DC accounts and b) Consumption – a broader measures which also includes Social Security wealth.

Wealth Our measure of wealth is the present discounted value of after-tax withdrawals facilitated by the account balance. We can express this as recursively, backwards from age 90. With $A_{i,90}^{j} = 0$, we define:

[45] This assumption ensures that interest rate we choose for discounting does not depend on patterns of withdrawals that we observe in our data.

$$A_{i,t}^{j}=\begin{cases}\frac{A_{i,t+1}^{DC}}{1+\hat{r}_{i,t+1}}+\left(w_{i,t+1}^{DC}-\tau_{i,t+1}^{w,DC}\right)-\left(dc_{i,t+1}^{ee}+dc_{i,t+1}^{er}-\tau_{i,t+1}^{c,BK}\right) & \text{for } j=DC,\\ \frac{A_{i,t+1}^{BK}}{1+\hat{r}_{i,t+1}}+\left(w_{i,t+1}^{BK}-\widehat{\tau_{i,t+1}^{r,BK}}\right)-\left(dc_{i,t+1}^{ee}+dc_{i,t+1}^{er}-\tau_{i,t+1}^{c,BK}\right) & \text{for } j=BK.\end{cases} \tag{23}$$

as the present value of future post-tax withdrawals less future post-tax contributions.

This is private retirement wealth and does not include wealth held in the form of Social Security benefits. We define Social Security wealth as:

$$SS_{i,t}=\frac{SS_{i,t+1}}{1+\hat{r}_{i,t+1}}+\left(ss_{i,t+1}-\tau_{i,t+1}^{ss}\right). \tag{24}$$

Our broad measure of wealth – which we refer to as consumption – takes into account both wealth in private accounts and Social Security wealth,

$$C_{i,t}=A_{i,t}^{DC}+C_{i,t}^{SS}, \tag{25}$$

B.8 Decomposing Retirement Wealth into its components

In this subsection we define how we decompose retirement wealth into three components: that which flows from employee contributions, that which can be ascribed to employer contributions, and that which is due to the favorable tax treatment of DC accounts.

B.8.1 Value of DC Tax Treatment

The total tax benefit to an individual i is defined as the difference between the retirement wealth of the DC saver and that of the brokerage saver.

$$A_i^T=A_{i,65}^{DC}-A_{i,65}^{BK}. \tag{26}$$

To find the retirement wealth concept attributable to the employee alone, we need to find, for each individual in our data, the proportion of contributions that are from the employee. The value at retirement of the contributions made by each of the employee and the employer are, respectively:

$$DC^{ee} = \sum_{t=25}^{65} dc^{ee}_{i,t}\left(\prod_{\tau=t}^{65}(1+\hat{r}_\tau)\right) \quad DC^{er} = \sum_{t=25}^{65} dc^{er}_{i,t}\left(\prod_{\tau=t}^{65}(1+\hat{r}_\tau)\right). \tag{27}$$

These can then be used to calculate the proportion of retirement wealth for the brokerage saver (i.e. after the tax benefits have been removed) which comes from employee contributions and employer contributions. These are, respectively:

$$A^{EE}_i = \frac{DC^{ee}}{(DC^{ee}+DC^{er})} \cdot A^{BK}_{i,65} \quad A^{ER}_i = \frac{DC^{er}}{(DC^{ee}+DC^{er})} \cdot A^{BK}_{i,65}. \tag{28}$$

The Treasury Department estimates the aggregate tax benefit given to DC savers in 2021 was $119 billion in 2021 (US Department of the Treasury (2023)). As a check on our model, we would like to compare our estimate of the tax benefit to the official estimate. Using an annuitization factor based on our model interest rate, we transform the mean lifetime tax benefit $A^T_i = \$52,936$ to an annual measure by dividing it by a factor of approximately 50. This results in a mean *annual* tax benefit of about $1,054. This estimate is for the population represented by our simulated data, where population DC coverage is estimated to be that for those currently in their 20s.[46] To convert our number to one which can be considered reflective of the current US population (who are the basis for the Treasury's numbers), we multiply our average annual tax benefit by the ratio of the DC savings rate in the population to the DC savings rate in the hotdeck sample. This ratio is around 1.5 and yields a comparable mean annual tax benefit to $694 per worker. Finally, we multiply this by an estimate of the civilian population engaged in work at any time in 2018 from the public CPS-ASEC, around 168 million people. Our model estimate of aggregate annual tax benefit to DC savers is then $117 billion.

B.9 Tax Counterfactual

The tax counterfactual considers the effect on retirement wealth and consumption if the aggregate associated tax expenditure were distributed proportionally to lifetime earnings. This would break the link between saving decisions and a worker's share of this tax expenditure but would not otherwise increase redistribution across lifetime income groups. That is, every individual would

[46] Our hotdeck imputation model matches younger people to older people based in part on DC access, the fact that younger people are more likely to have access to DC plans will make DC access more prevalent in our sample than in the population.

receive a government contribution to her DC account calculated as a proportion of her lifetime earnings. This proportion is uniform across all individuals and chosen so that the total cost of these government contributions matches the total cost incurred under the existing tax-favored system.

Let the value of lifetime total earnings be:

$$LE_i = \sum_{t=25}^{65} (comp_{i,t}) \left(\prod_{\tau=t}^{65} (1 + \hat{r}_\tau) \right) \tag{29}$$

where $comp_{i,t} = e_{i,t} + dc_{i,t}^{ee}$ is the sum of earnings and deferred compensation. We define a redistributed tax advantage that allocates the total tax benefit in the economy so that it is proportional to lifetime income:

$$A_i'^{T} = \frac{LE_i}{\sum_n LE_n} \cdot \sum_n A_n^T \tag{30}$$

where the first term is an individual's share of aggregate lifetime earnings and the second term is the aggregate tax expenditure. We assume no behavioral response to the change in the tax treatment of retirement contributions so that employee and employer contributions are unchanged. We indicate with a $'$ superscript aggregates under this counterfactual. Retirement wealth and retirement consumption in this counterfactual are therefore equal to:

$$A_i'^{DC} = A_i^{EE} + A_i^{ER} + A_i'^{T} \qquad C_i' = SS_i + A_i'^{DC}$$

B.10 Match Counterfactual

In the presence of an employer match for retirement contributions, those who save more receive higher total compensation from their employer. Our employer match counterfactual breaks this link and considers the effect of a noncontingent employer contribution that is proportional to employee earnings. Every worker would receive an employer contribution to her DC account proportional to her current earnings, regardless of whether she makes a contribution. This percentage would be the same for all workers under the same employer but would vary across employers. It is selected so that the total cost of employer contributions for a given employer equals the total cost that this employer incurs under its existing matching formula.

For our employer-match counterfactual, we calculate the proportional contribution that, if given to all employees in the firm, would cost the same to the firm as their actual matching contributions. That is, for each time period t we calculate the ratio of total matching contributions to total income for each firm and multiply that by individual income. Denoting as i an employee working in firm f with an employer match of $dc_{i,t}^{er}$,[47] instead of receiving $dc_{i,t}^{er}$ in period t, the employee receives:

$$dc_{i,t}^{*er} = \frac{comp_{i,t}}{\sum_{n \in f} comp_{i,t}} \cdot \sum_{n \in f} dc_{n,t}^{er} \tag{31}$$

where the first term is individual i's share of compensation in their firm in period t and the second term is the aggregate matching contributions made by their employer in period t. We then calculate all modeled objects as described above assuming that, instead of their actual employer match contributions ($dc_{i,t}^{er}$) each period, employees receive the counterfactual match $dc_{i,t}^{*,er}$. Accounting for this and for the fact that trajectories of taxation will be different, will yield different levels of wealth at retirement. All stocks in this model are denoted as in the baseline model but with the addition of a $*$ superscript. We denote the counterfactual contributions from employers and due to the tax expenditure as ($A_i^{*,ER}$ and A_i^{*T}), respectively., so that the new levels of wealth and consumption in retirement are equal to:

$$A_i^{*DC} = A_i^{EE} + A_i^{*ER} + A_i^{*T} \qquad C_i^* = SS_i + A_i^{*DC} \tag{32}$$

B.11 Combined Counterfactual

Our combined counterfactual equalizes both the employer match contribution and the tax subsidy. To do this first obtain the brokerage saver's wealth under the employer match counterfactual $C_{i,t}^{\dagger BK}$. We add to the redistributive tax subsidy calculated in tax counterfactual ($A_i^{\dagger ER}$). Denoting

[47]This will be linked to the employee's contribution ($dc_{i,t}^{ee}$) by a function that gives the employer match: $dc_{i,t}^{er} = m_f(dc_{i,t}^{ee})$.

all aggregates under the combined counterfactual with an † superscript (though note that $A_i^{\dagger ER} = A_i^{*ER}$), we obtain:

$$A_i^{\dagger DC} = A_i^{EE} + A_i^{\dagger ER} + A_i^{\dagger T} \qquad C_i^{\dagger} = SS_i + A_i^{\dagger DC} \tag{33}$$

B.12 Parameterization

B.12.1 Rates of return

Total investment return is given by an age-varying interest rate r_t. Each age t is associated with a portfolio composition between equities, bonds, and bills, parameterized by σ_t^k, σ_t^b, and σ_t^m. During working years, these shares are interpolated from Fidelity target date funds (see, for example, the 2040 Target Date Fund in Fidelity (2023)). In retirement, we assume exclusive investment in bonds. The age-profile of investment composition is shown in Figure C.33a, and the associated age-profile of real rate of return is shown in Figure C.33b. Real rates of return for these asset types (ρ^k, ρ^b, and ρ^m, respectively) are taken from Jordà et al. (2019). The combination of these assumptions yields age-specific rates of return r_t according to

$$r_t = \rho^k \cdot \sigma_t^k + \rho^b \cdot \sigma_t^b + \rho^m \cdot \sigma_t^m. \tag{34}$$

Note in retirement that $r_t = \rho^b$. We derived the decomposition of returns into these shares by studying the historical price trends and distributions of the Fidelity Freedom Funds Fidelity (2023).[48]

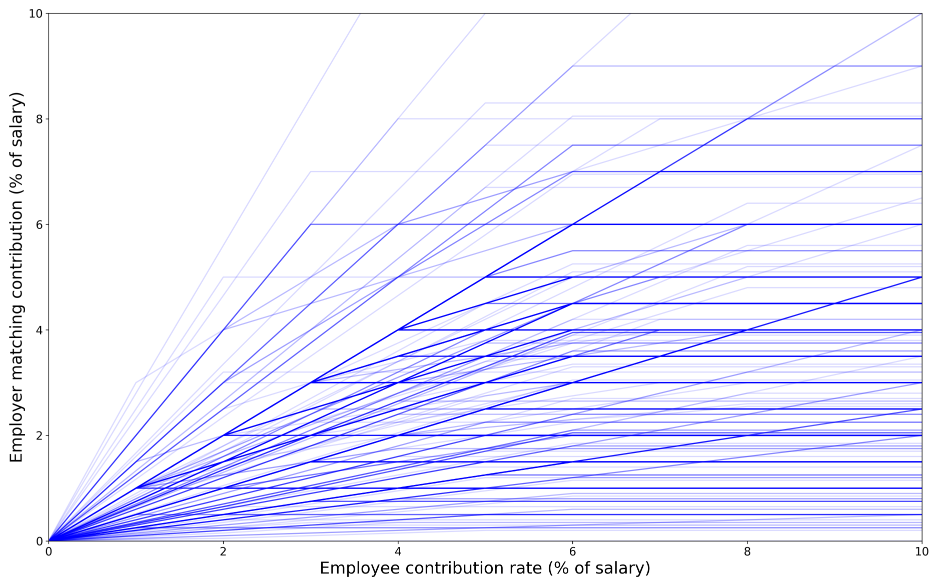
[48] Our breakdown of 50% price change, 40% distribution taxed as long-term capital gains, and 10% taxed as income is very similar to the 48/43/9 breakdown found by Sialm and Zhang (2020), under the assumption that 95% of dividends are non-qualified.

Appendix Figures

C Appendix Figures

C.1 Supplemental Figures to Section 2

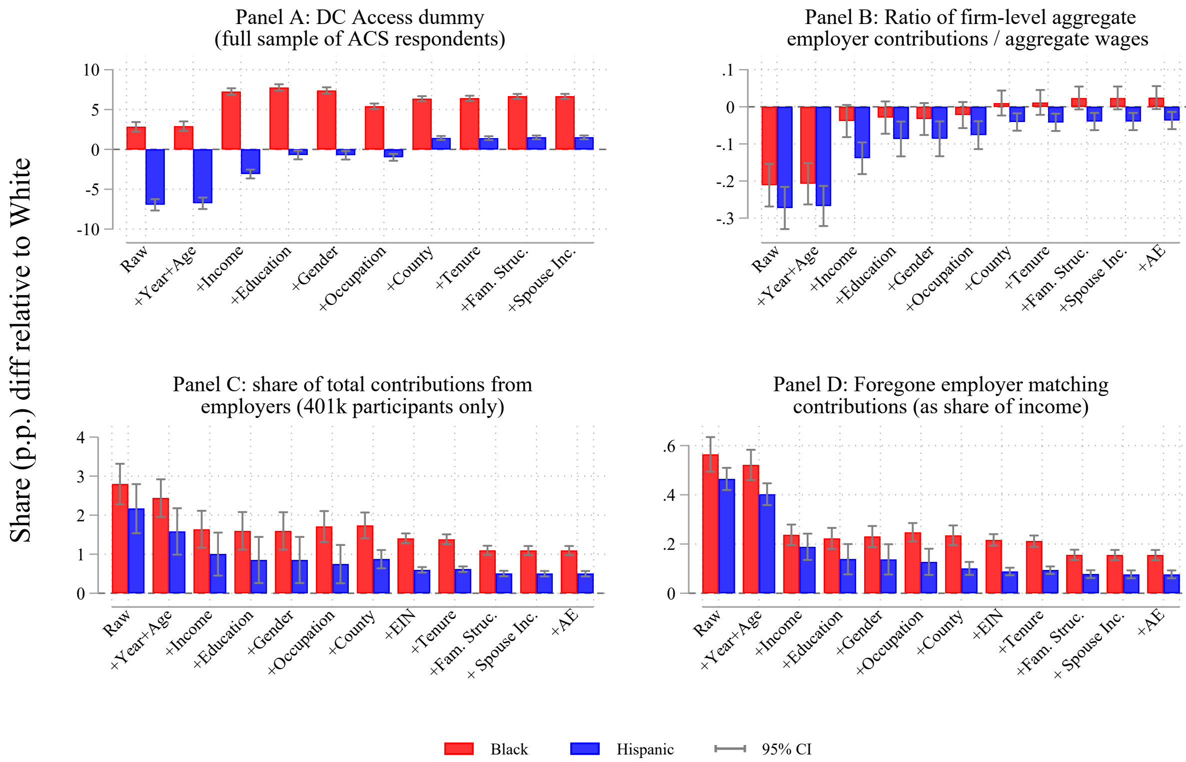
Figure C.1: Matching schedules



Notes: The sample is all employer match schedules for plans in a particular year. Each line represents a match schedule, and the depth of shade represents the frequency of the match schedule.

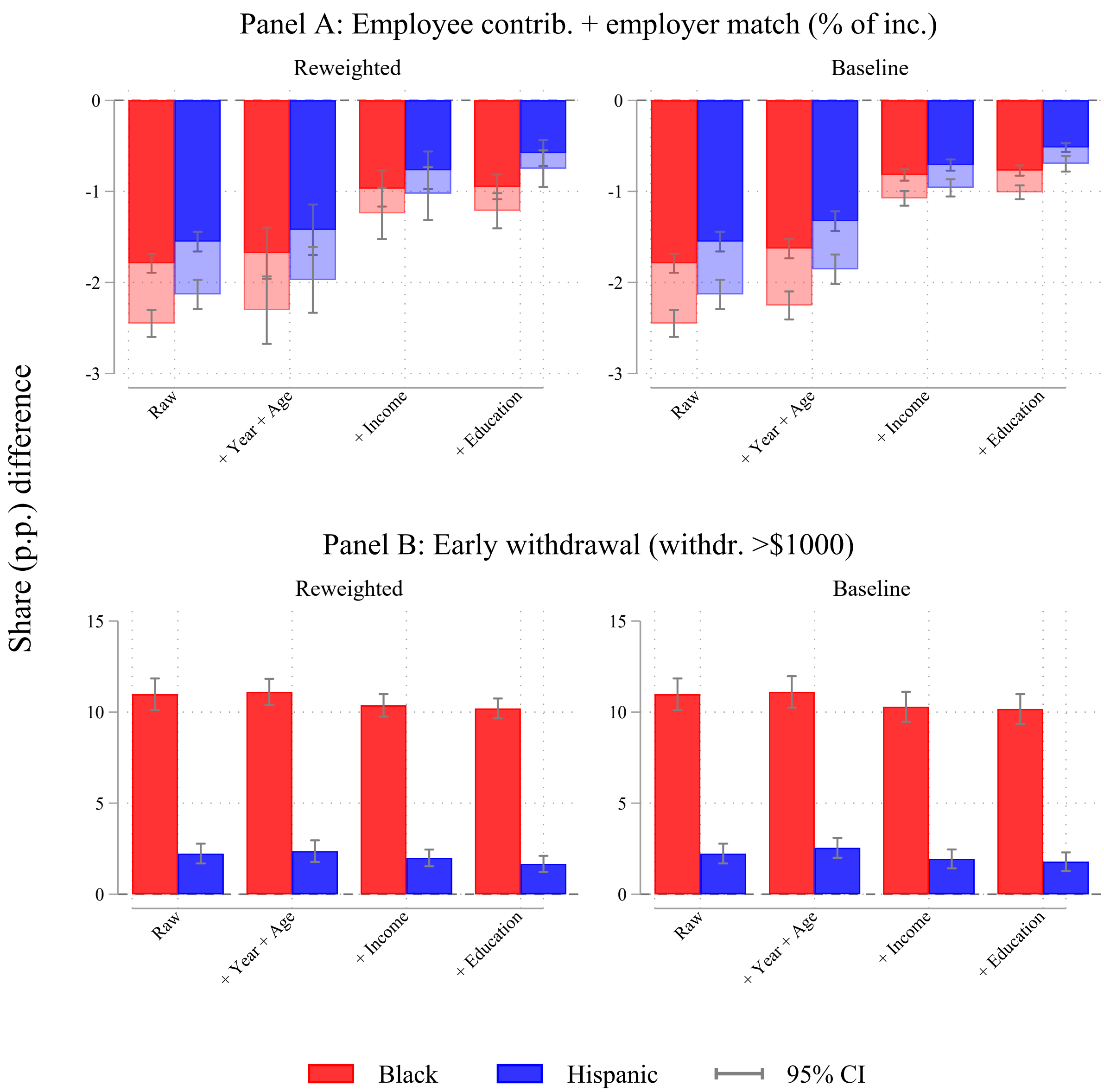
C.2 Supplemental Figures to Section 4

Figure C.2: Decomposing DC plan accessibility and savings by race



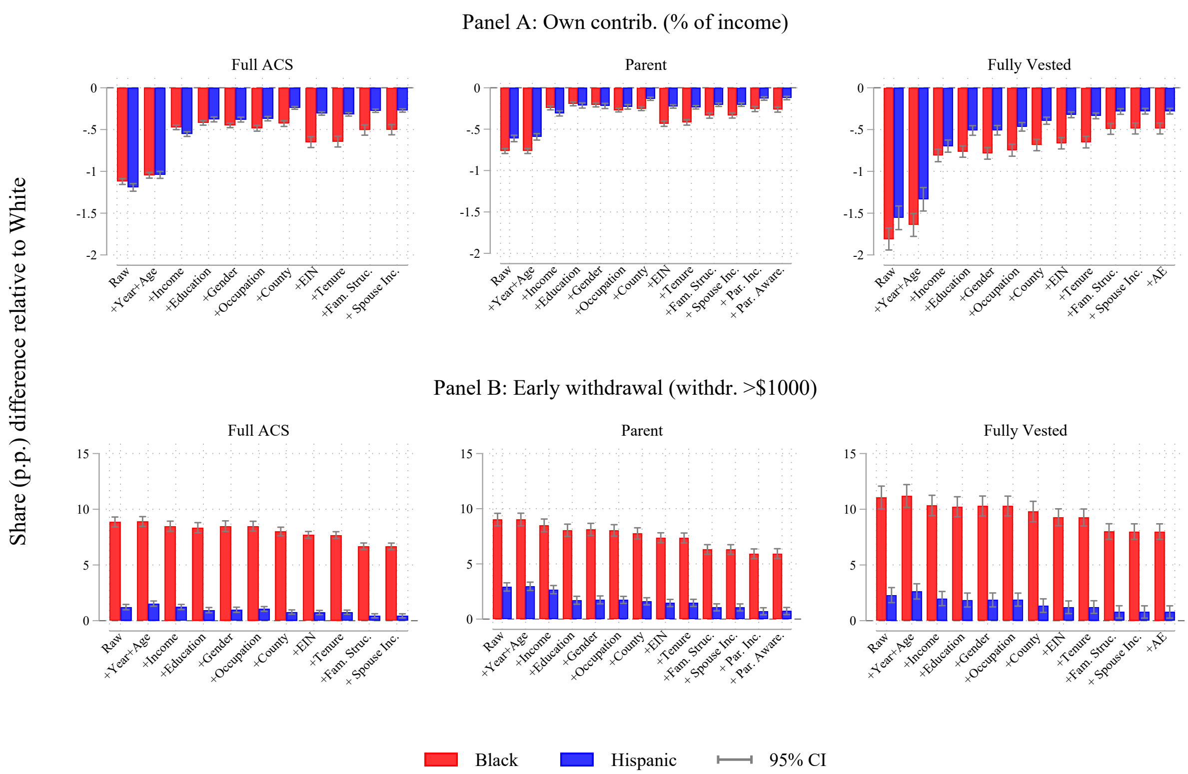
Notes: Panel A presents accessibility to DC plans by race. Panel B shows the ratio of firm-level aggregate employer contributions divided by total employee compensation for each firm ($\frac{aggregate\_employer\_match}{aggregate\_employer\_match+aggregate\_employee\_deferred\_compensation}$). Panel C shows the share of total contributions at the individual-level ($\frac{employer\_match}{employer\_match+employee\_DC}$). Panel D shows the foregone employer matching contributions (as a share of total income). We use the specification defined in Equation 1, omitting EIN for Panels A and B due to perfect collinearity.

Figure C.3: Racial gap estimates re-weighted using the characteristic shares of White employees



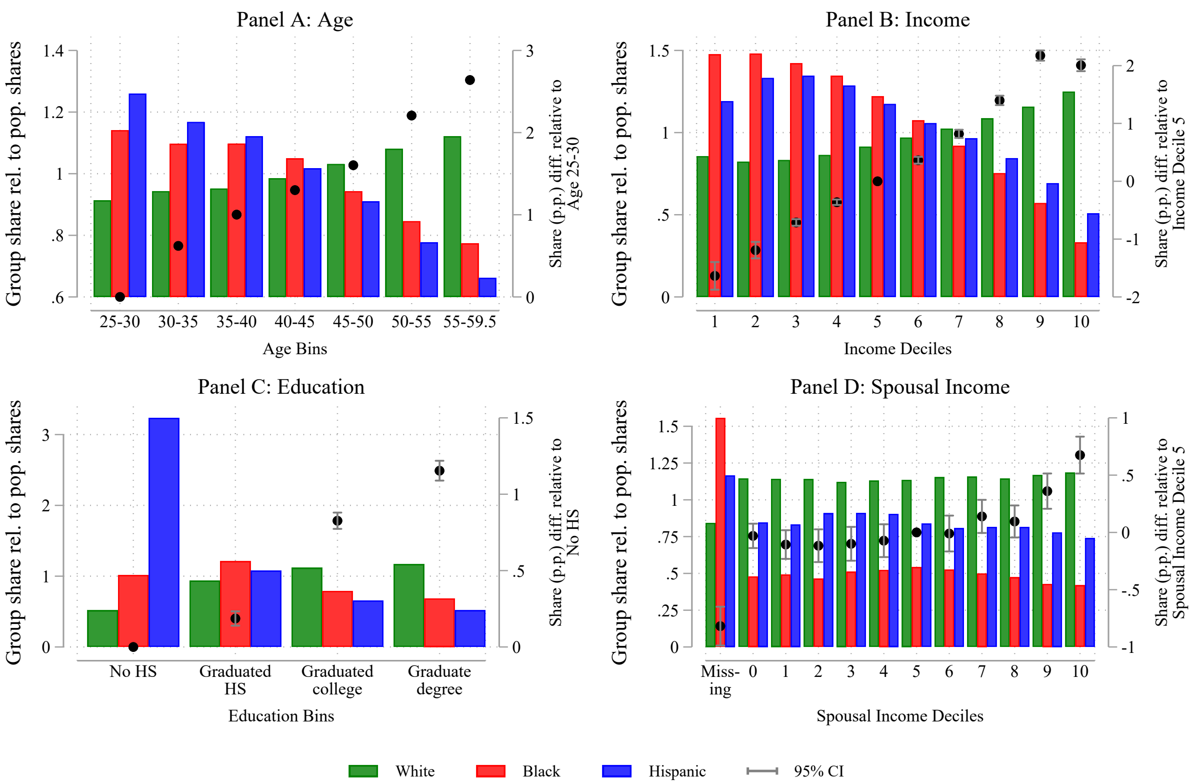
Notes: This figure presents a robustness check of our main results. We re-weight the Black and Hispanic worker distributions according to the White worker distribution. The left column of figures presents gaps for our reweighted matching sample gaps; the right column of figures presents gaps for our matching sample results, as presented in Figure 2. We use the progressive specification defined in Equation 1. Due to cell size constraints in U.S. Census disclosure requirements, we present estimates for the first five regression controls, from raw gaps through gender. Panel A shows the employee contribution in opaque bars and overlays the employer match in transparent bars. Panel B shows the early withdrawal rates.

Figure C.4: Racial gap estimates across samples



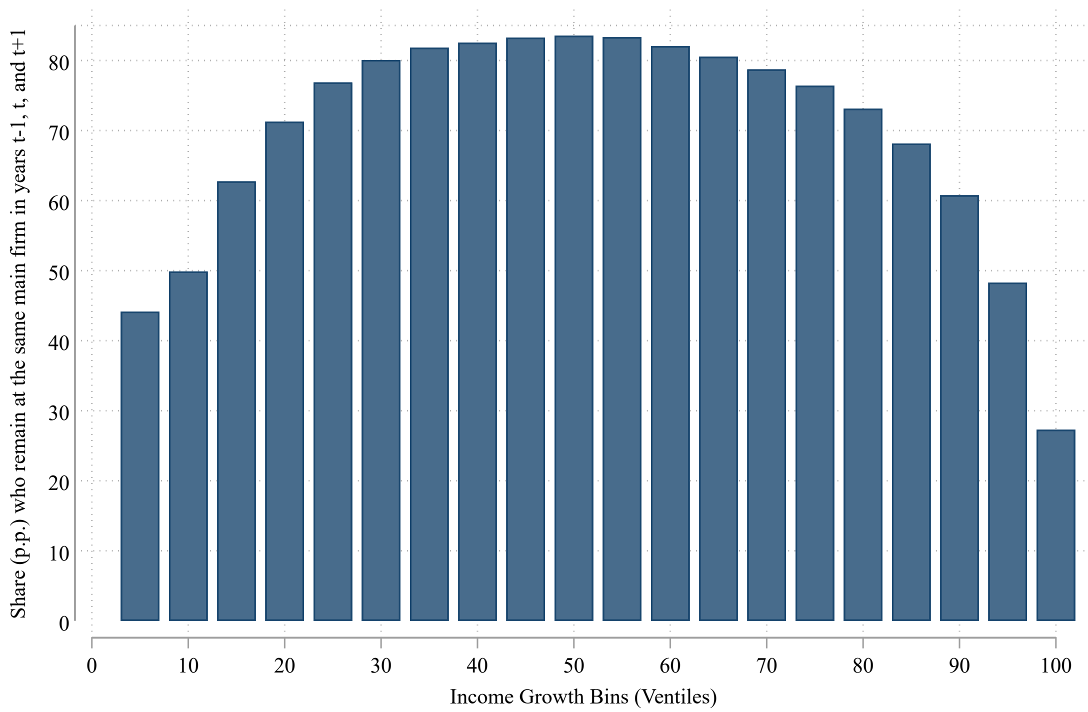
Notes: This figure presents robustness checks for our main results (Figure 2). We use the progressive specification (Equation 1) for our full ACS sample of employees, our parent sample (without retirement plan matches), and our vesting sample (restricting on fully-vested employees). Panel A presents the employee contribution rate; Panel B presents early withdrawals. Coefficients are relative to White.

Figure C.5: Regression coefficients and groups shares



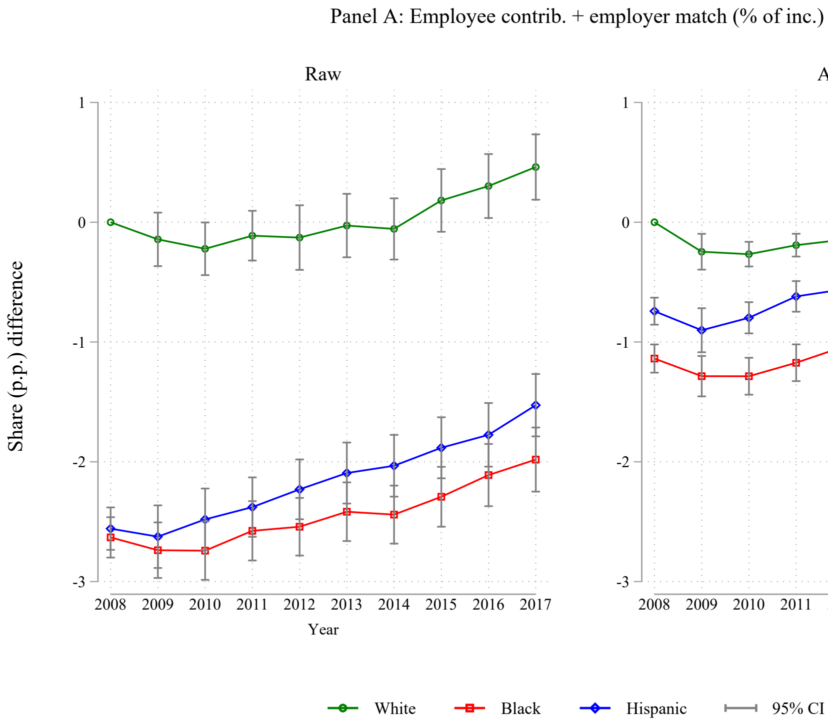
Notes: This figure presents i) the racial composition (bars, right axes) and ii) the regression coefficients (dots, left axes), from our fully saturated model (defined in Equation 1) for four important mediating channels: age (Panel A), income (Panel B), education (Panel C), and spousal income (Panel D). The regression outcome is employee contribution plus employer matching rate (% of income). Appendix A.1.3 provides definitions for the outcome and mediating channels. The racial composition for each bin corresponds to Panel B in 6, while the coefficient estimates correspond to Panel C in 6. The coefficients are provided in column 1 of Table 3.

Figure C.6: Share of workers who stay at their firm across the income growth distribution



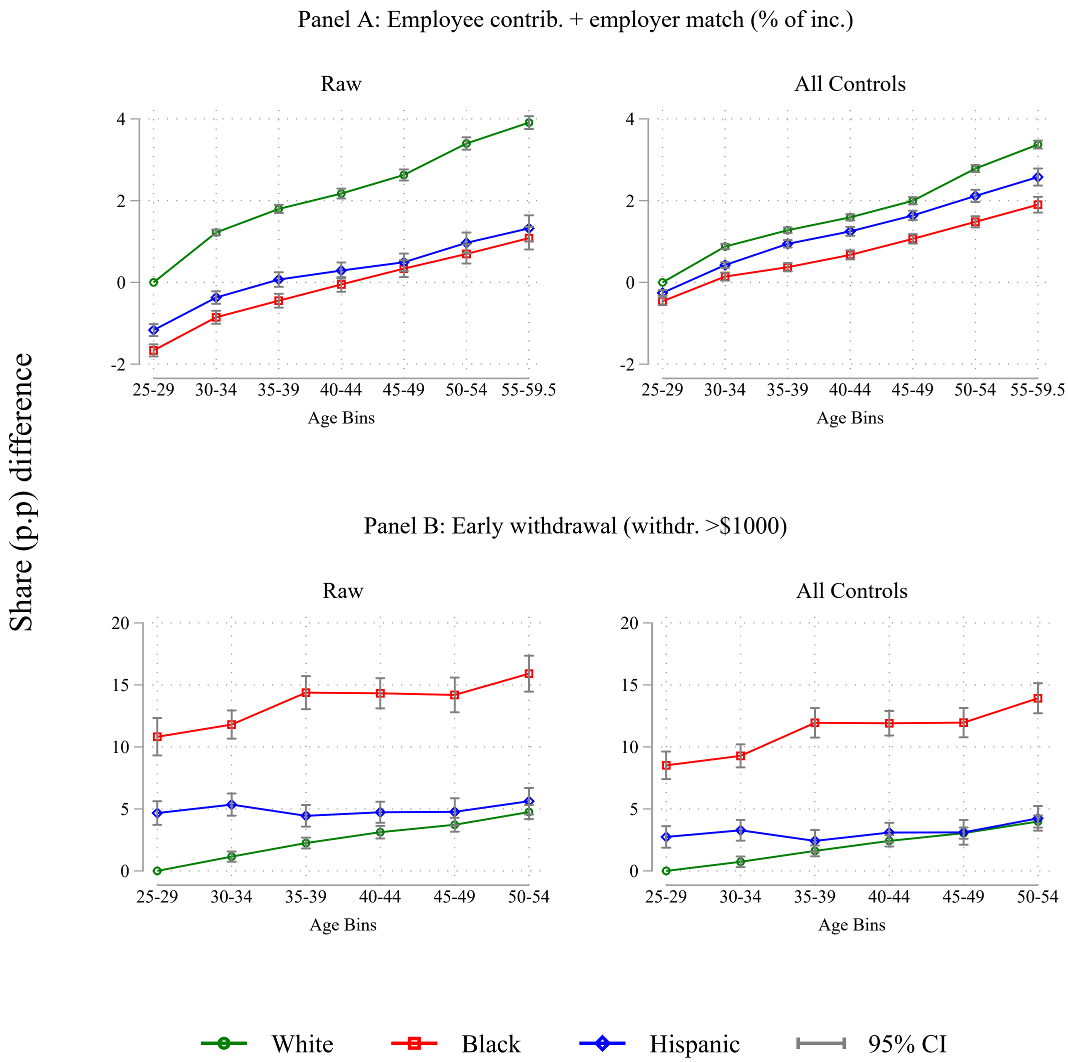
Notes: Of the ACS respondents we observe in year t and who satisfy our requirements to be in the early withdrawal sample, we plot the share of workers who remain at the same main firm (i.e., the firm who pays them the most) in years $t-1$, t, and $t+1$.

Figure C.7: Racial savings gaps by year



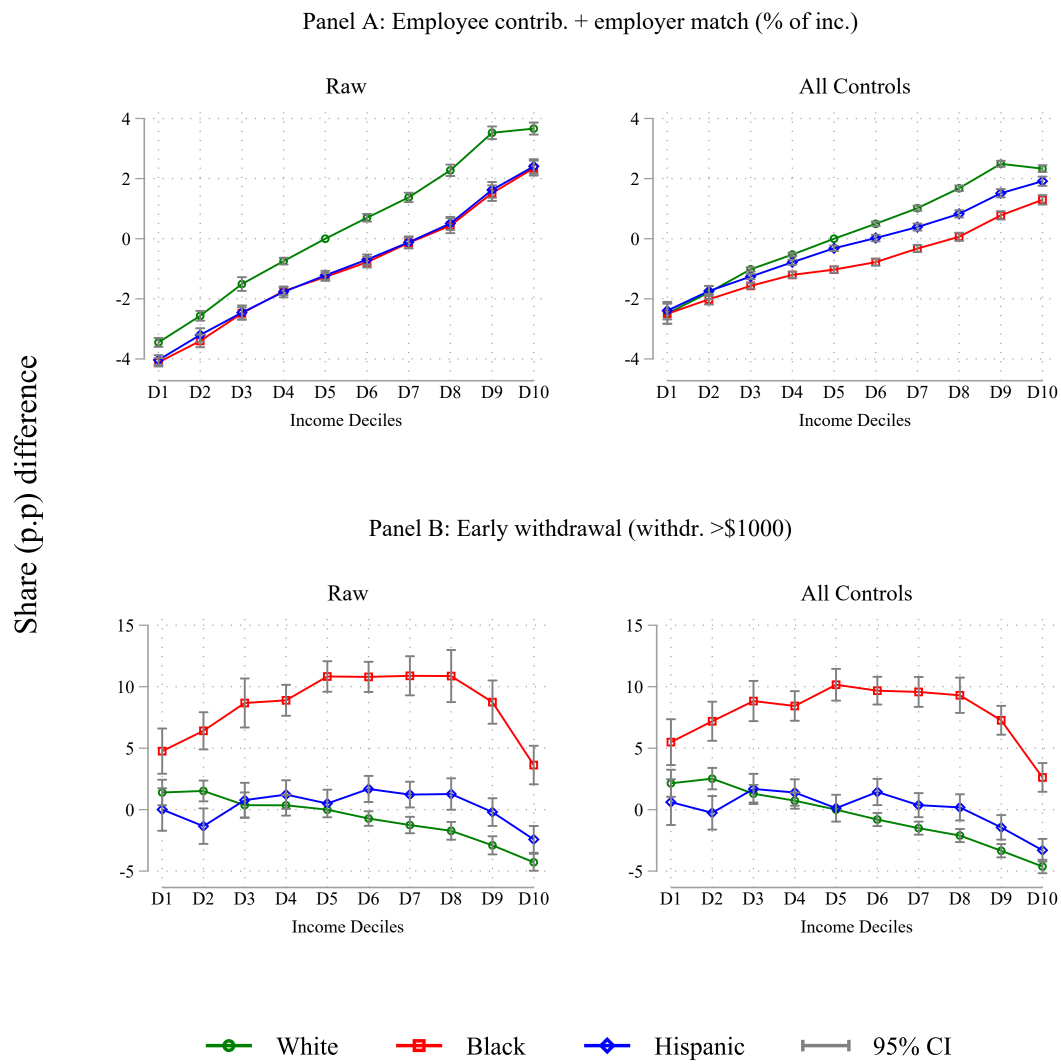
Notes: This figure presents the racial gaps in employee contribution plus employer match rates for each year from 2008-2017. The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 year_t + \zeta(year_t \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(year_t \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.8: Racial savings gaps and leakage by age



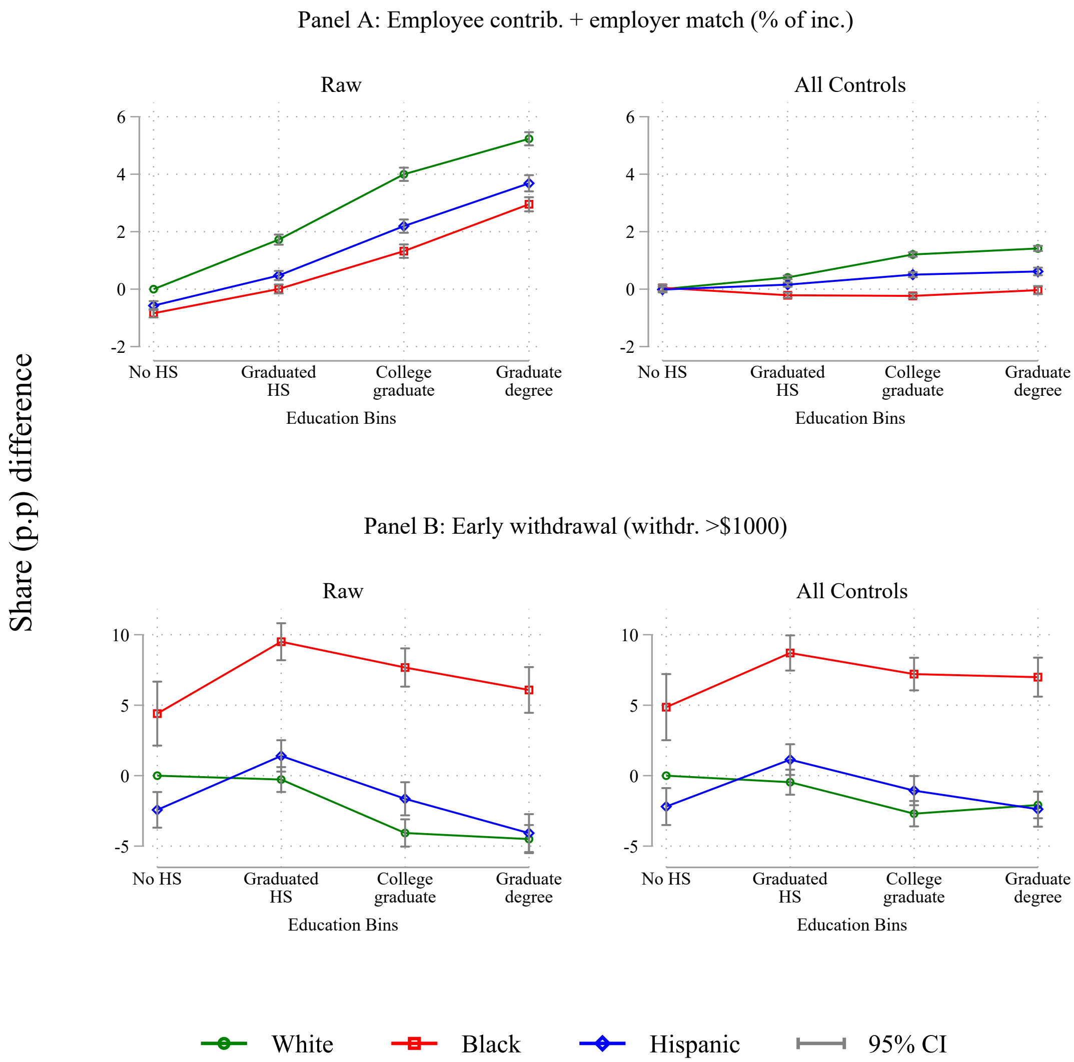
Notes: This figure presents the racial gaps in savings and leakage by age. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >\$1,000). The left column shows disparities for our raw specification without other mediating channels. The model is $y_{it} = \alpha + \beta_1 age\_i + \zeta(age\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regressions include mediating channels that interact with race. These are year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(year_t \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.9: Racial savings gaps and leakage by income



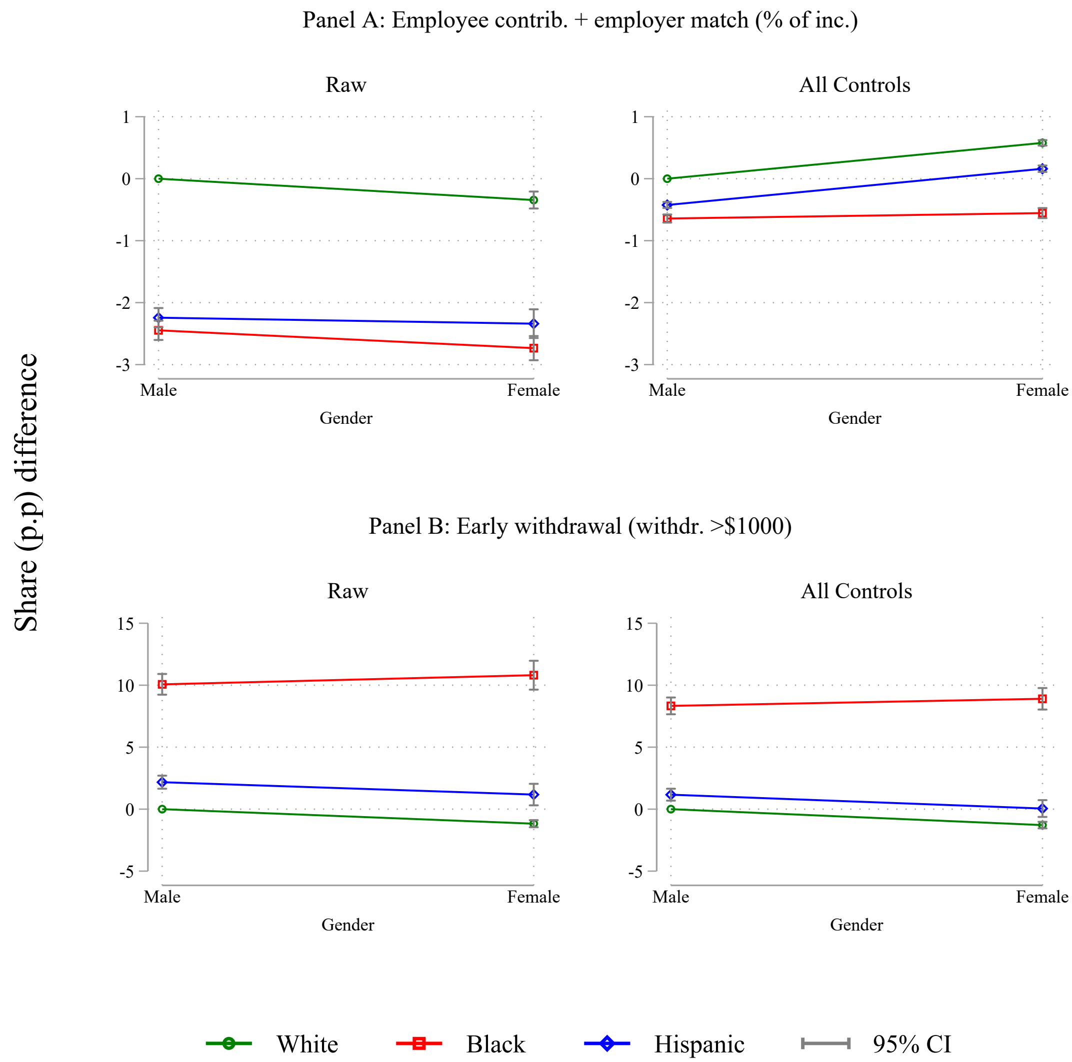
Notes: This figure presents the racial gaps in savings and leakage by income. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >\$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 incomebin\_i + \zeta(incomebin\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educbin_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(incomebin\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.10: Racial savings gaps and leakage by education



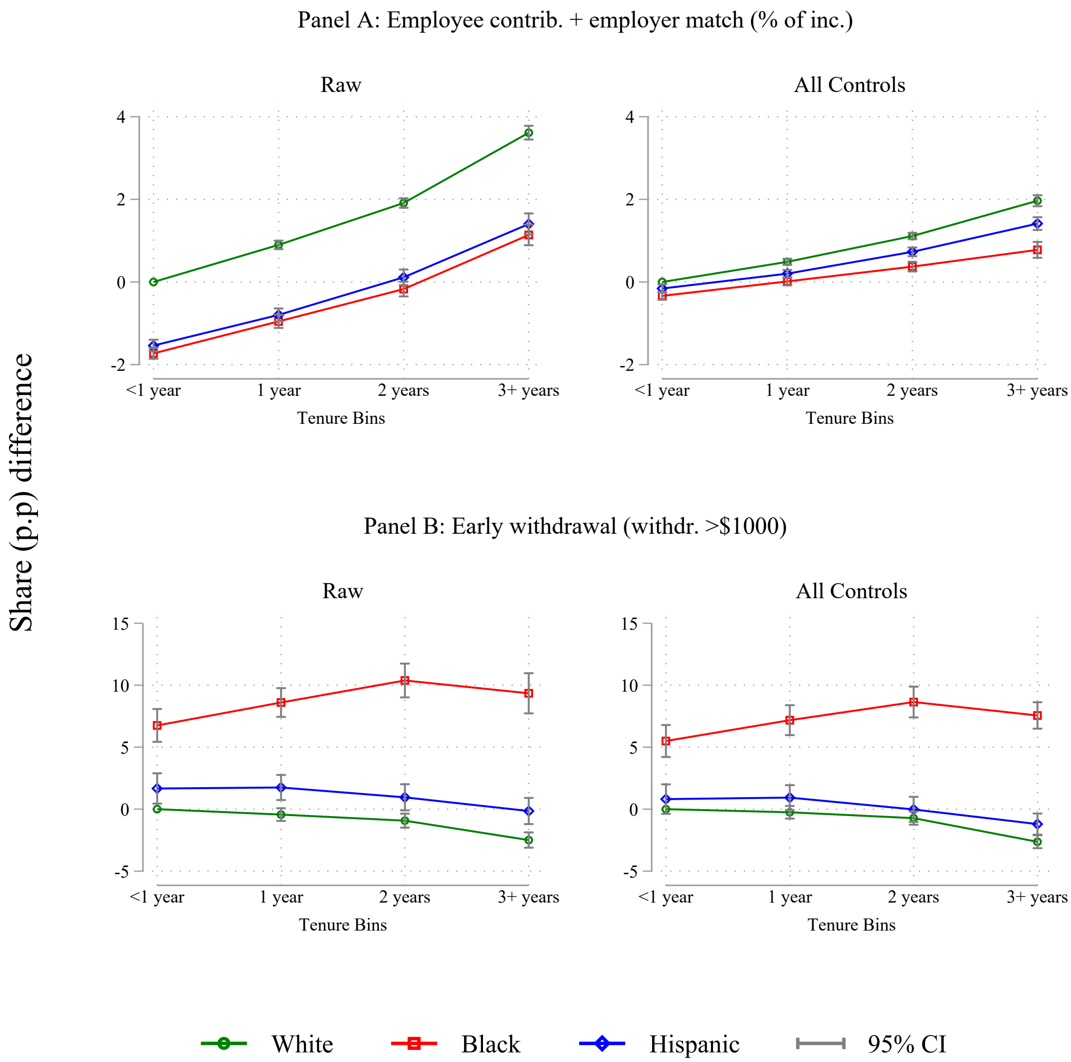
Notes: This figure presents the racial gaps in savings and leakage by education. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 educ\_i + \zeta(educ\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(educ\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.11: Racial savings gaps and leakage by gender



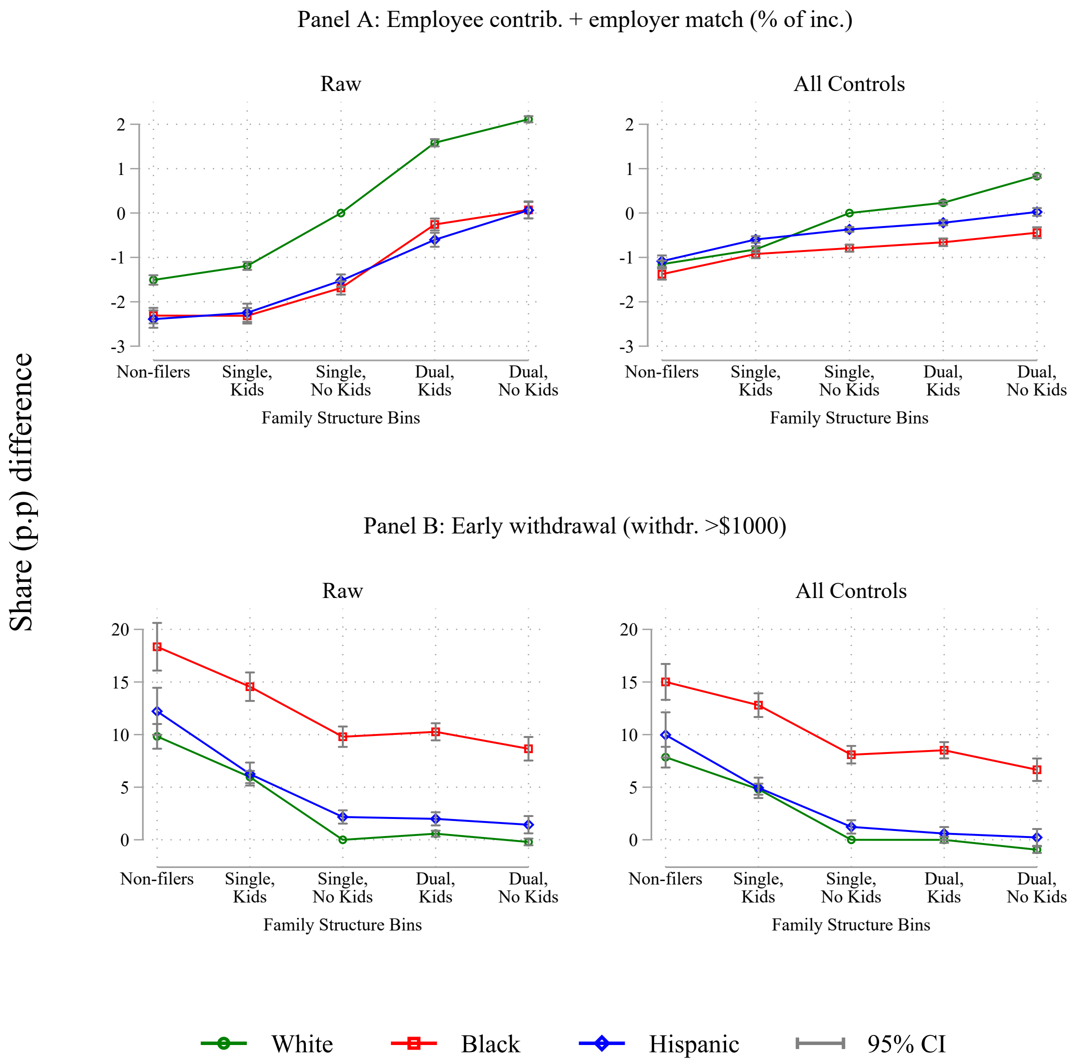
Notes: This figure presents the racial gaps in savings and leakage by gender. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 female\_i + \zeta(female\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(female\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.12: Racial savings gaps and leakage by tenure



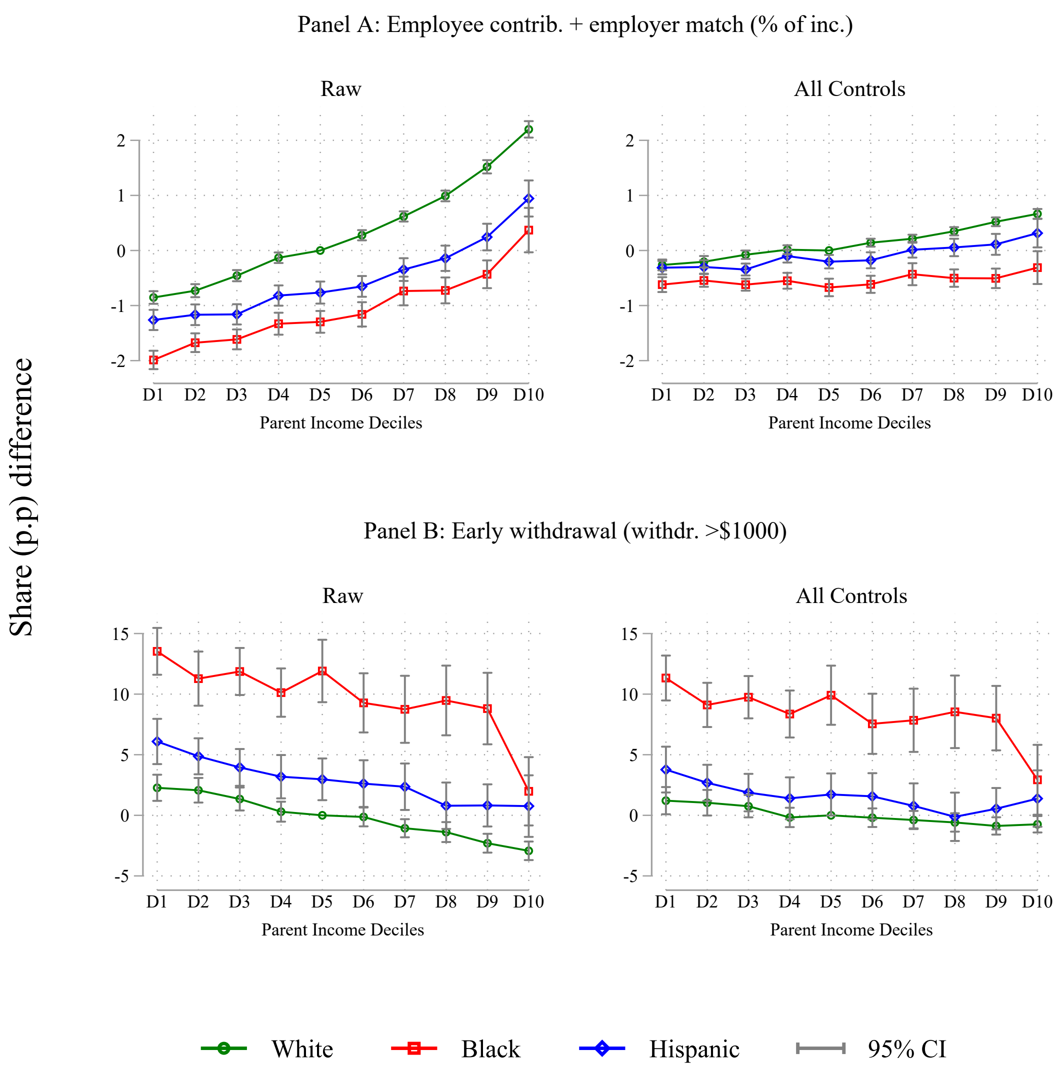
Notes: This figure presents the racial gaps in savings and leakage by tenure. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 tenure\_i + \zeta(tenure\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(tenure\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.13: Racial savings gaps and leakage by family structure



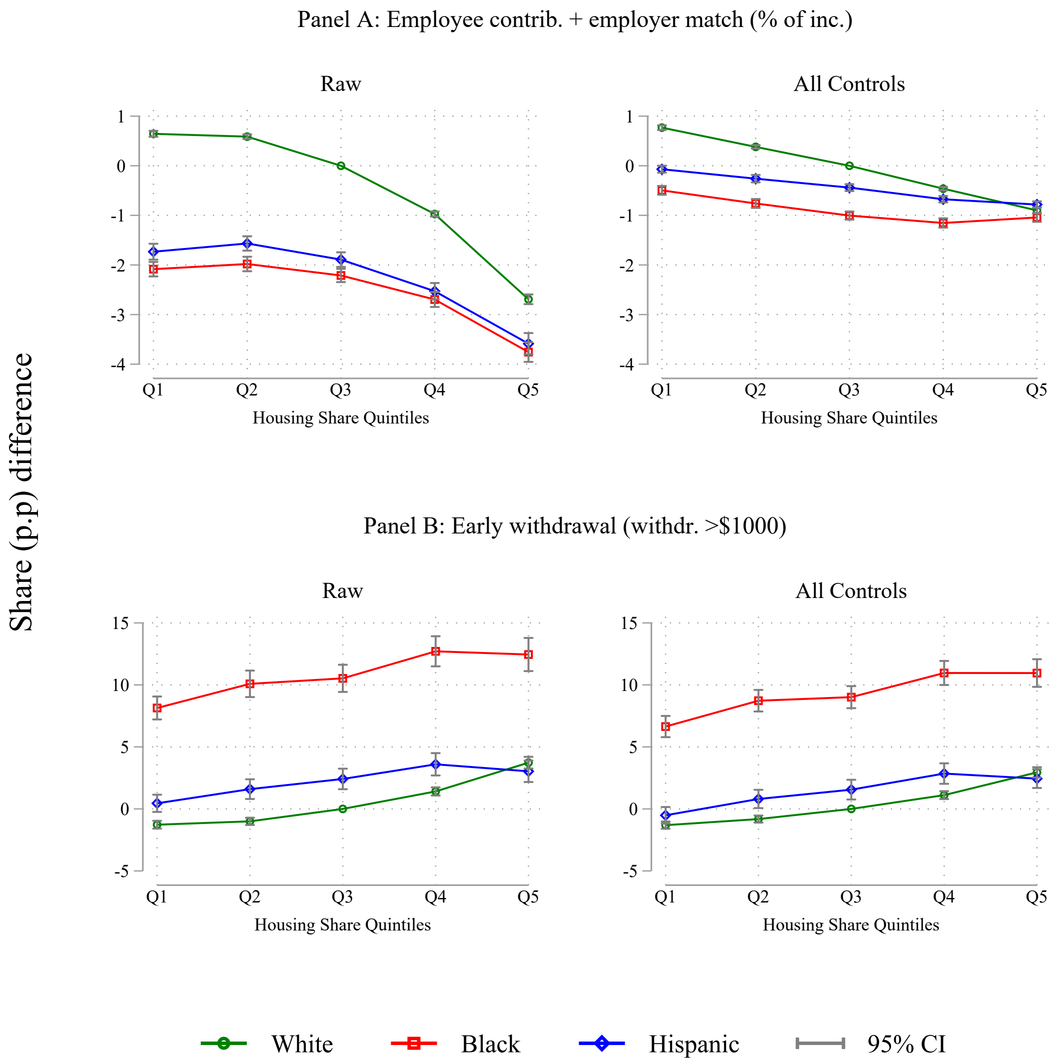
Notes: This figure presents the racial gaps in savings and leakage by family structure. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 familystructure\_i + \zeta(familystructure\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(familystructure\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.14: Racial savings gaps and leakage by parent income



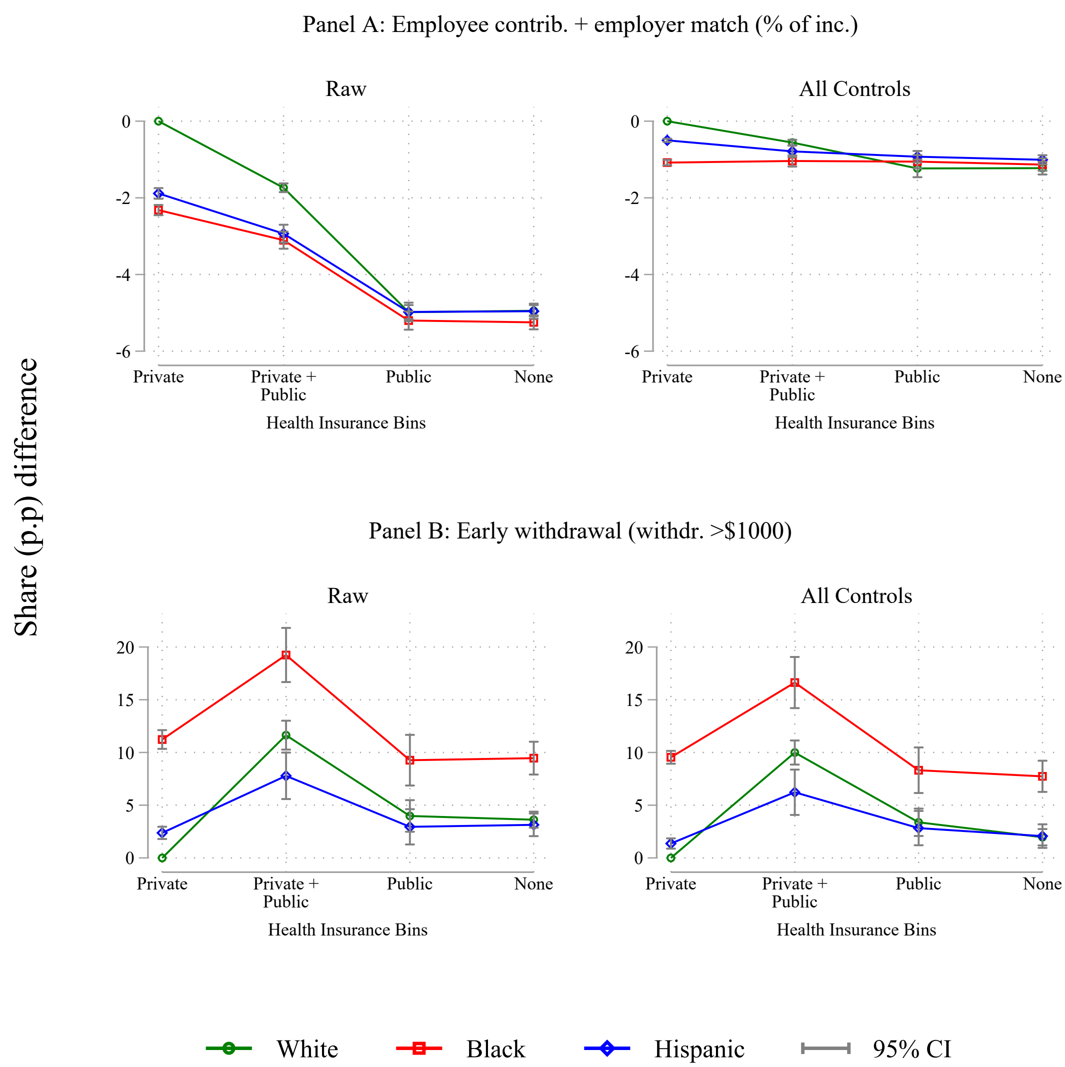
Notes: This figure presents the racial gaps in savings and leakage by parent income. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 parentincomebin\_i + \zeta(parentincomebin\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(parentincomebin\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.15: Racial savings gaps and leakage by housing as a share of income



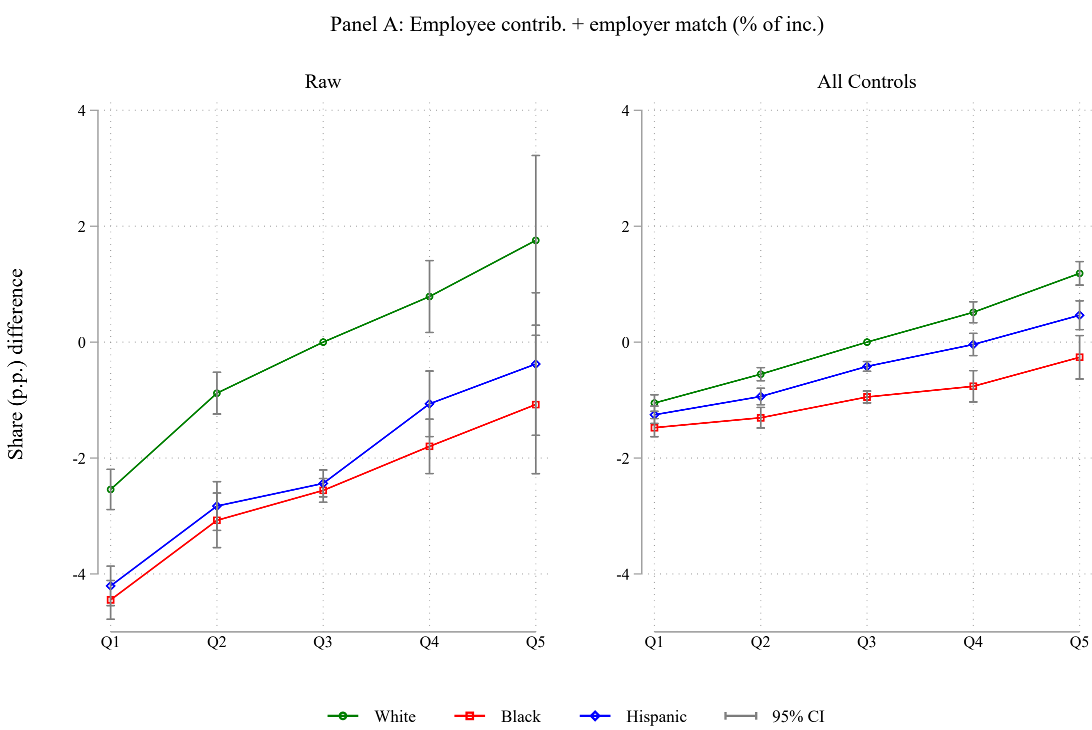
Notes: This figure presents the racial gaps in savings and leakage by housing as a share of income. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 housingsharebin\_i + \zeta(housingsharebin\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(housingsharebin\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.16: Racial savings gaps and leakage by health insurance



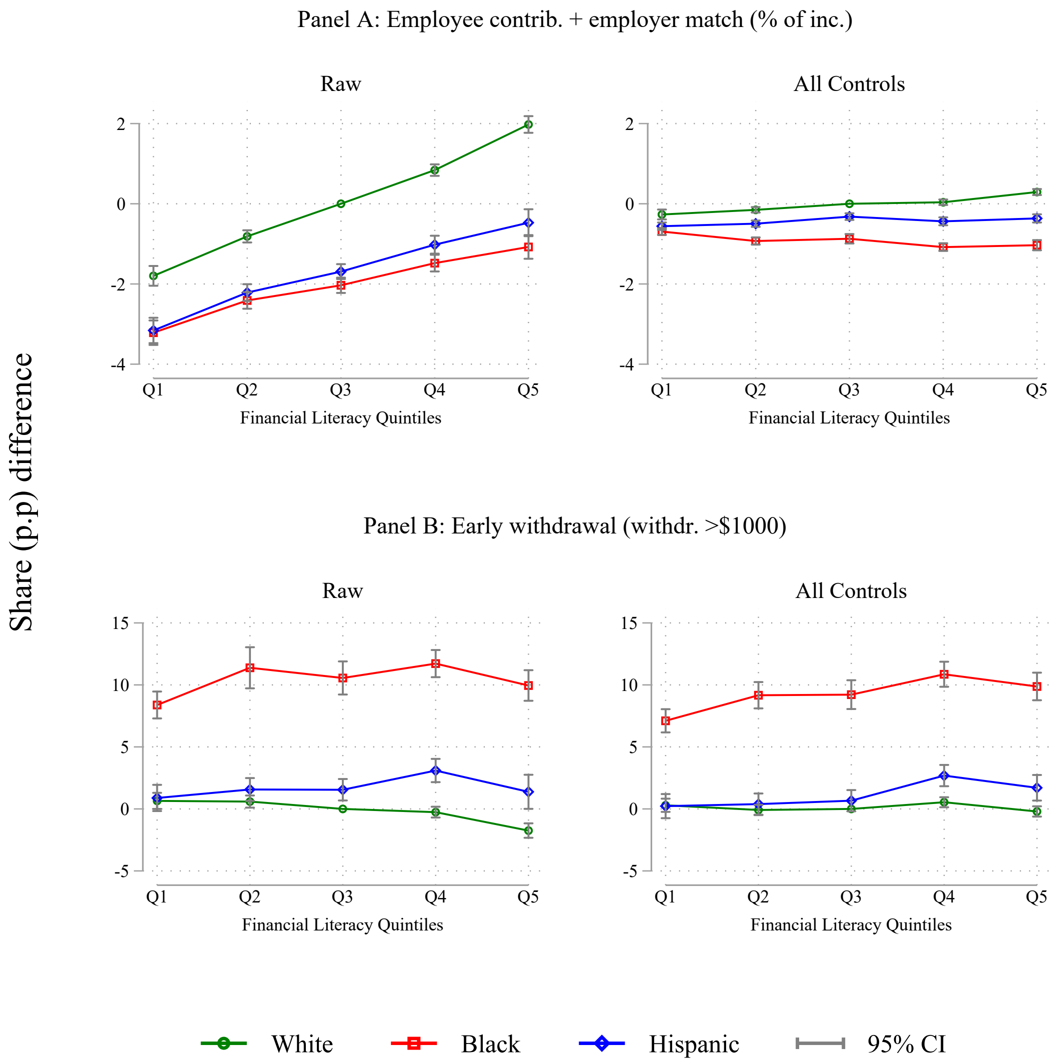
Notes: This figure presents the racial gaps in savings and leakage by health insurance. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 healthinsurance\_i + \zeta(healthinsurance\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(healthinsurance\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.17: Racial savings gaps and leakage by maximum employer match



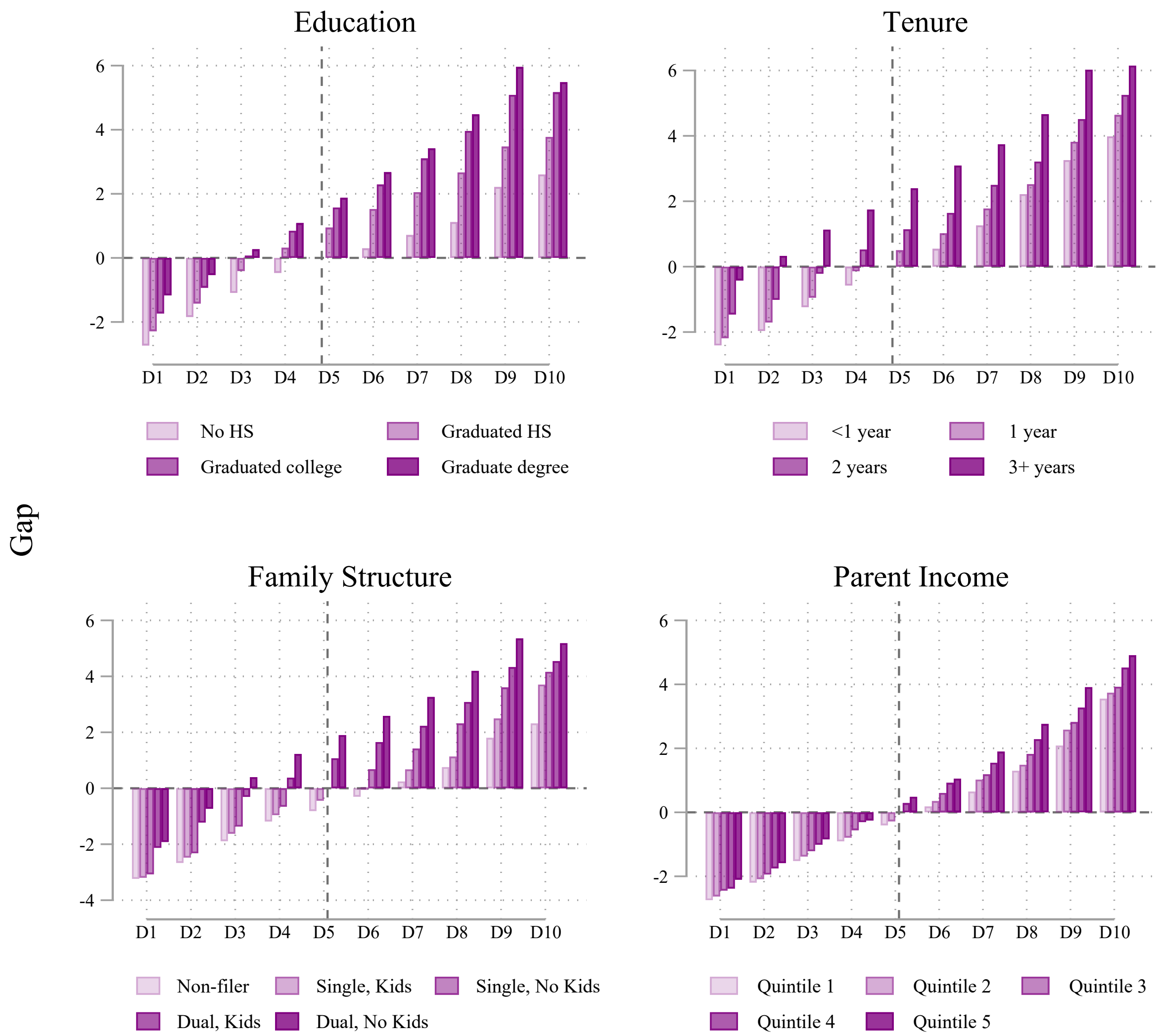
Notes: This figure presents the racial gaps in savings and leakage by the maximum employer match. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 max\_employer\_match\_bin\_i + \zeta(max\_employer\_match\_bin\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \gamma_{occupation} + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(max\_employer\_match\_bin\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. See Figure 3 for more details.

Figure C.18: Racial savings gaps and leakage by financial literacy



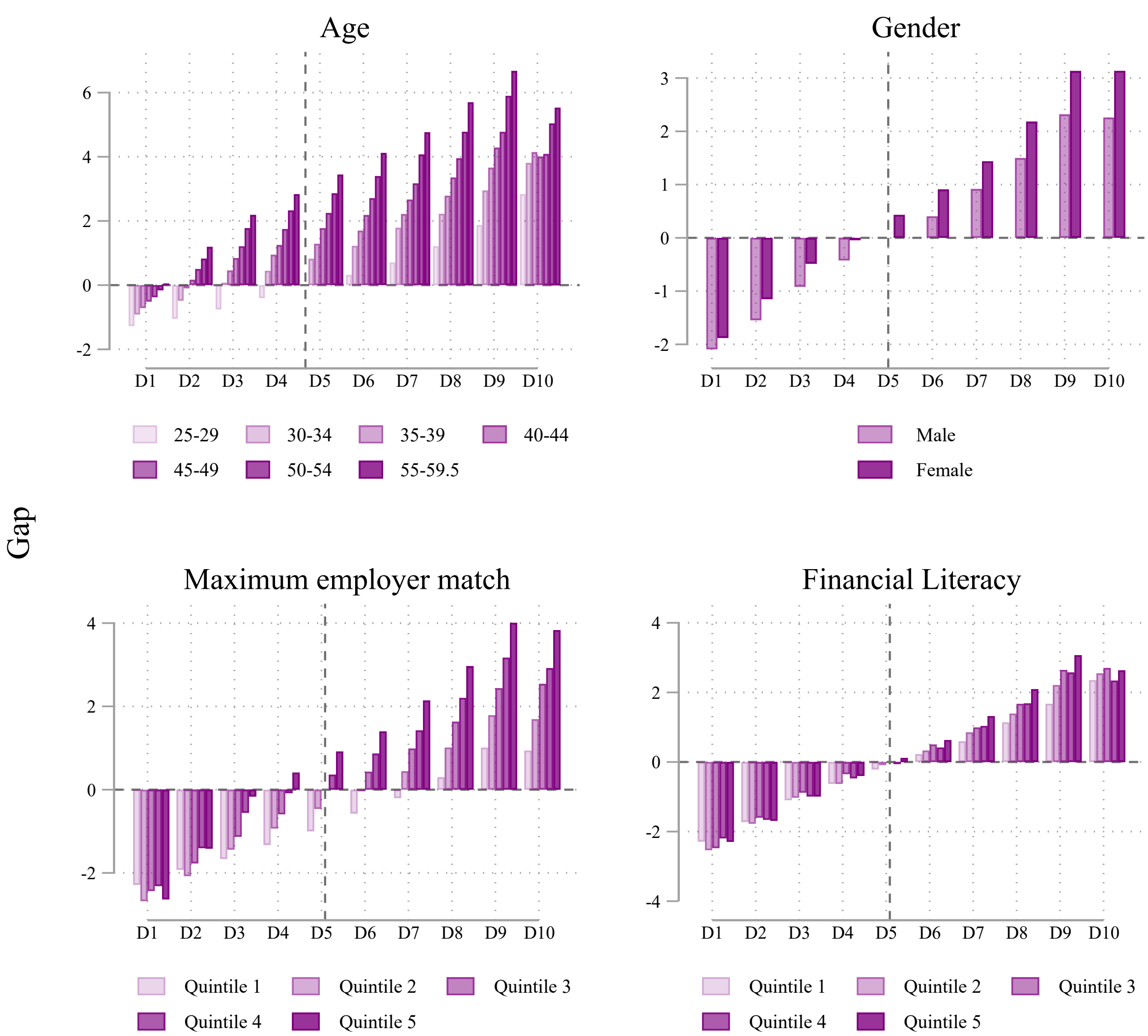
Notes: This figure presents the racial gaps in savings and leakage by financial literacy. Panel A shows disparities in employee contribution plus employer match rates. Panel B shows disparities in early withdrawal rates (conditional on withdrawals >$1,000). The left column shows disparities for our raw specification without independent variables. The model is $y_{it} = \alpha + \beta_1 financial\_literacy\_bin\_i + \zeta(financial\_literacy\_bin\_i \cdot race_i) + \epsilon_{it}$. The right column shows the disparities for our fully-saturated model. Regression variables include dummies for year, age, income, education, gender, occupation, county, EIN, and tenure. Our model is $y_{it} = \alpha + \beta_1 year_t + \beta_2 agebin_i + \beta_3 incomebin_i + \beta_4 educ_i + \beta_5 female_i + \delta_{county} + \lambda_{EIN} + \beta_6 tenure_i + \zeta(financial\_literacy\_bin\_i \cdot race_i) + \epsilon_{it}$. ζ provides our coefficients of interest. 95% confidence intervals are included; standard errors are clustered by EIN. We drop occupation fixed effects due to perfect collinearity. See Figure 3 for more details.

Figure C.19: Savings gaps by income interacted with demographics, raw



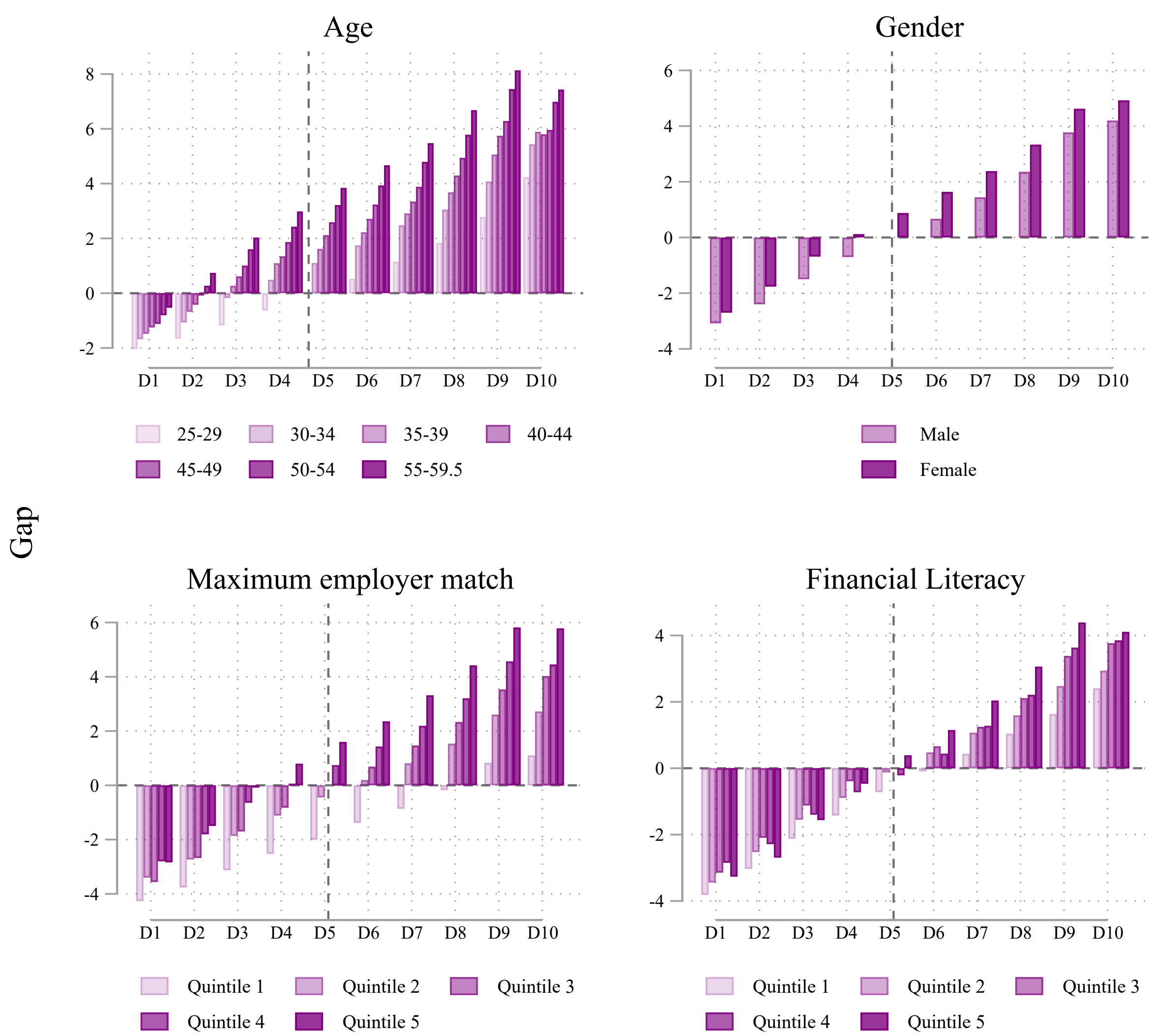
Notes: This panel is the raw version of Figure 8, excluding all dummies. It shows gaps in employee plus employer matched contribution rates by different covariates and income deciles, relative to individuals in the 5th income decile who are in our selected base category (e.g., education bin "No HS" for our education variable). The dashed line indicates the base category. Beginning clockwise from the top left, we have age, education, family structure, parent income, tenure, and maximum employer match. Each group of bars corresponds with an income decile. Each individual bar represents the group of people in that income decile. The legend defines each category. Our model resembles our main specification, but includes an interaction between income and our control variable of choice. Our model is $y_{it} = \alpha + \zeta(variable_i \cdot incomebin_i) + \epsilon_{it}$

Figure C.20: Savings gaps by income interacted with demographics, fully saturated



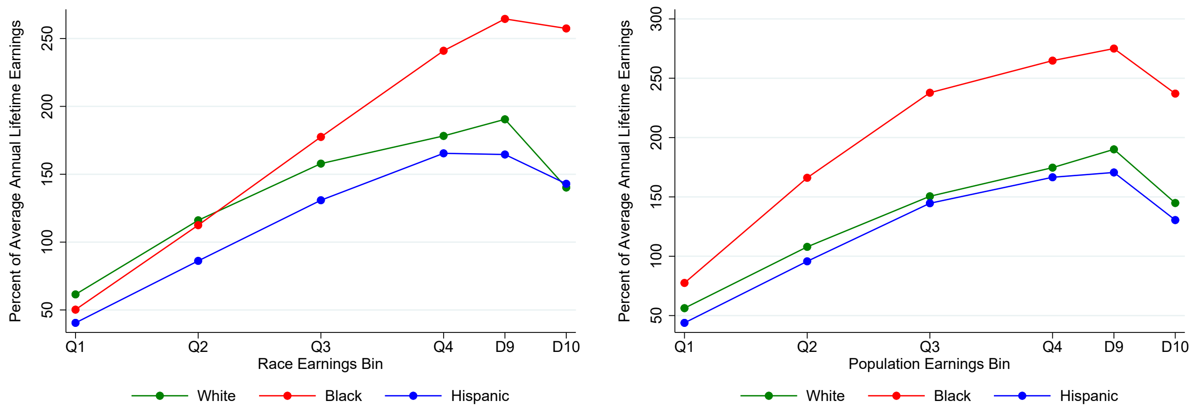
Notes: This figure presents other important mediation channels, using the same model as Figure 8. It shows gaps in employee plus employer matched contribution rates by different covariates and income deciles, relative to individuals in the 4th income decile who are in our selected base category (e.g., age bin "25-30" for our age variable). Important mediation channels, in counter-clockwise direction, are age, gender, financial literacy, and maximum employer match. Our model includes an interaction between income and our mediating channel of choice. We include dummies for year, age, education, gender, occupation, county, EIN, and tenure. It omits occupation fixed effects for financial literacy due to the that our financial literacy measure is at the firm level.

Figure C.21: Savings gaps by important mediation channels, raw



Notes: This panel is the raw version of Figure C.20, excluding all dummies. It shows gaps in employee plus employer matched contribution rates by different covariates and income deciles, relative to individuals in the 4th income decile who are in our selected base category (e.g., age bin "25-30" for our age variable). The dashed line indicates the base category. Beginning clockwise from the top left, we have age, education, family structure, parent income, tenure, and maximum employer match. Each group of bars corresponds with an income decile. Each individual bar represents the group of people in that income decile. The legend defines each category. Our model includes an interaction between income and our mediating channel of choice. It omits occupation fixed effects for financial literacy due to perfect collinearity.

Figure C.22: Value of withdrawals at retirement by race and earnings



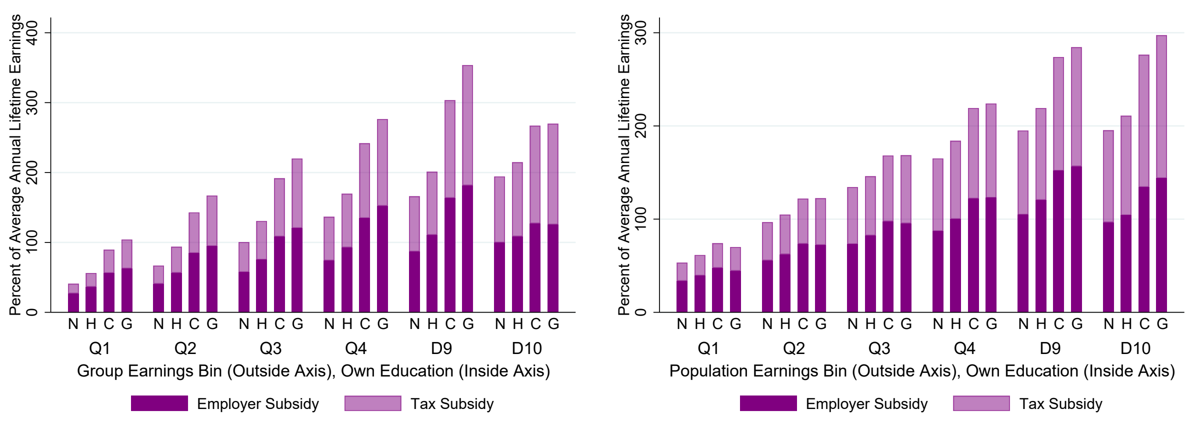
(a) By own-group quintiles

(b) By population quintiles

This figure shows the future value at retirement of all pre-retirement withdrawals as a percentage of average annual lifetime earnings. These amounts are graphed by race and earnings quintiles calculated on the entire population, with the top quintile split into two deciles.

C.3 Supplemental Figures to Section 7

Figure C.23: Contrib. of employer and tax subsidies to retirement wealth, by education

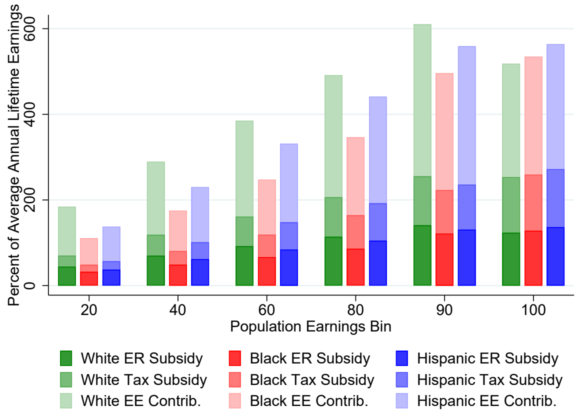


(a) By own-group quintiles

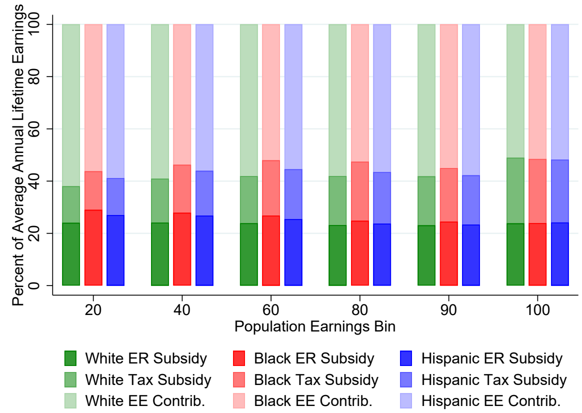
(b) By population quintiles

Notes: This figure follows the format as Figures 11 and 12, but by own education instead of race or parental income. Education levels are no high school, graduated high school, graduated college, or graduate degree. The darker bars are the value at retirement of all employer matches, accounting for any pre-retirement withdrawals. The lighter bars are the value at retirement of the various tax advantages given to DC accounts throughout the life cycle. These amounts are divided by average annual lifetime earnings in order to standardize comparisons across earnings levels. Education levels are graphed by earnings quintiles, with the top quintile split into two deciles. Panel A has quintiles calculated within each race group, while Panel B's quintiles are calculated across own-education groups.

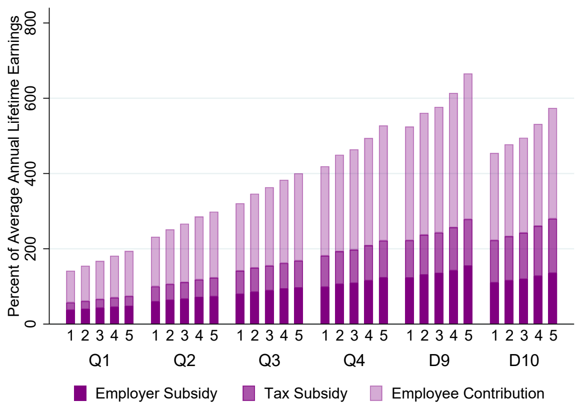
Figure C.24: Contrib. of employer and tax subsidies to retirement wealth



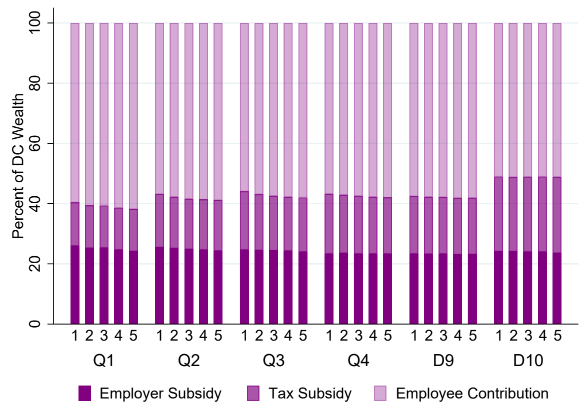
(a) By race and population income group, \$



(b) By race and population income group, %



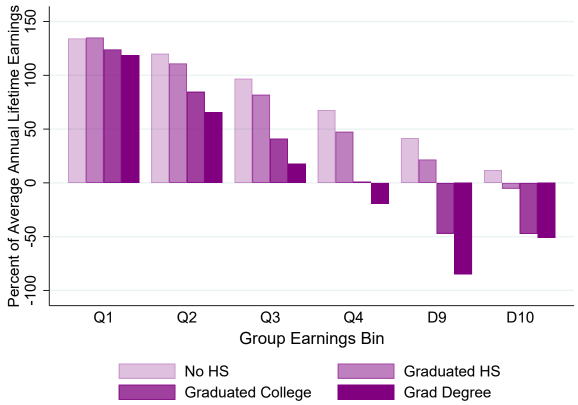
(c) By parental income and own pop. income group, \$



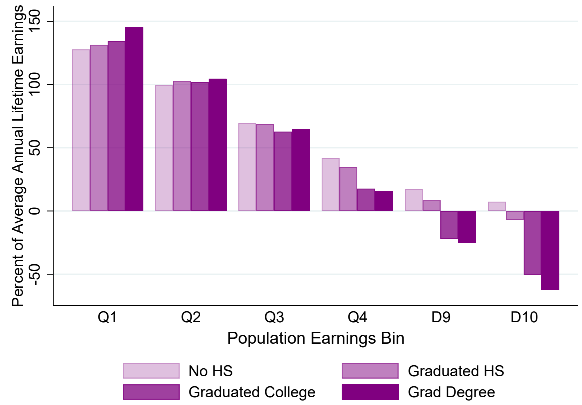
(d) By parental income and own pop. income group, %

Notes: This figure follows the format as Figures 11 and 12, but with the addition of employee contribution to wealth at retirement. The bottom (darkest) bars are employer match, then tax subsidy, then employee contribution, representing all the components of wealth at retirement. All panels show splits by quintiles calculated on population lifetime earnings, with the last quintile split into two deciles. Panels A and B show subsidies by race, while Panels C and D show splits by parental income quintile. Panels A and C show all variables as a percentage of average annual lifetime earnings, while Panels B and D show variables as a percentage of wealth at retirement (which sum to 100).

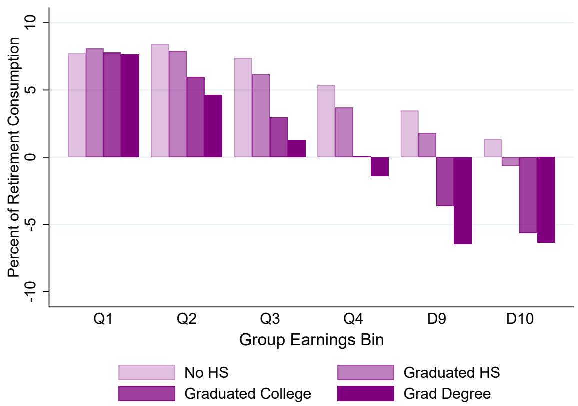
Figure C.25: Change in retirement wealth and consumption, by education



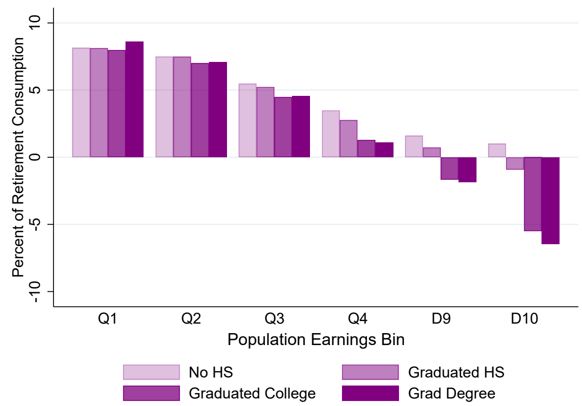
(a) Δ wealth, by education, own group quintiles



(b) Δ wealth, by education, pop. quintiles



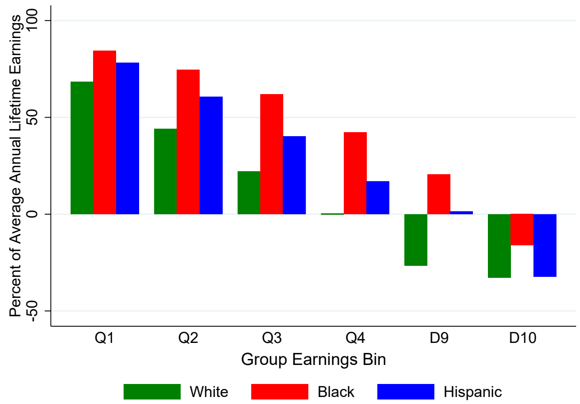
(c) Δ cons., by education, own group quintiles



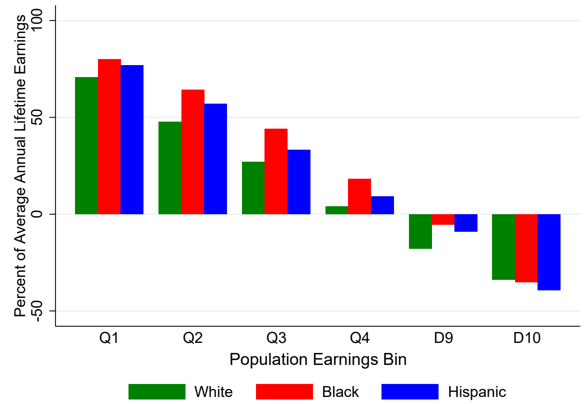
(d) Δ cons., by education, pop. quintiles

Notes: This figure is in the same format as Figures 13 and 14, but by own education instead of race or parental income. Education levels are no high school, graduated high school, graduated college, or graduate degree. This figure illustrates the impact of our baseline counterfactual exercise on wealth on retirement and consumption in retirement. This counterfactual exercise distributes the aggregate employer matches in each firm so that all workers in that firm receive the same proportion of their earnings, and distributes the aggregate federal tax expenditure so that all workers receive a contribution that is in proportion to their lifetime earnings. We show the effect on two outcomes: the top two panels (A and B) show the change in DC wealth on retirement, with wealth expressed as a proportion of average annual working life earnings. The bottom two panels (C and D) show proportionate change in consumption in retirement (where consumption is the sum of DC wealth and Social Security). For both DC wealth and consumption, we show results by two different types of lifetime earnings bins. The graphs on the left (Panels A and C) form lifetime earnings bins within education group. In the graphs on the right (Panels B and D) the bins represent population groups. In each case, lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles.

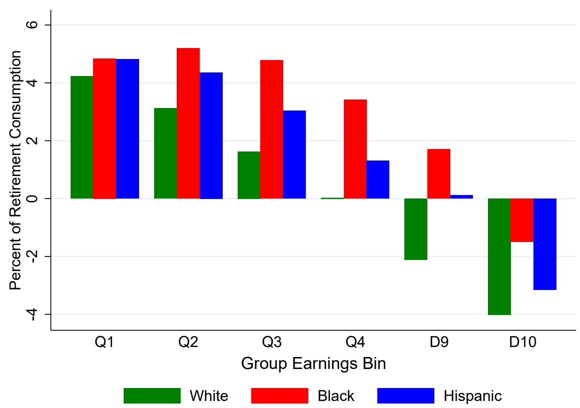
Figure C.26: Change in retirement wealth and consumption under tax counterfactual, by race



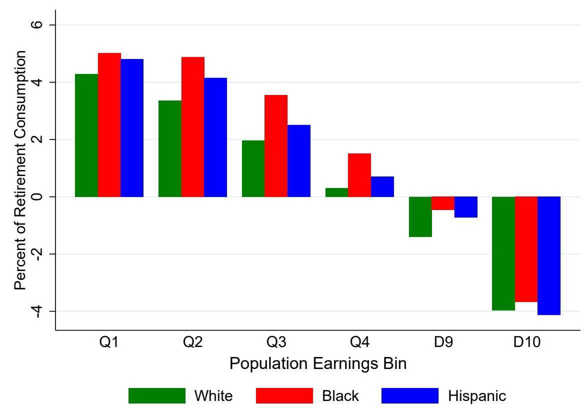
(a) Change in ret. wealth, own race quintiles



(b) Change in ret. wealth, pop. quintiles



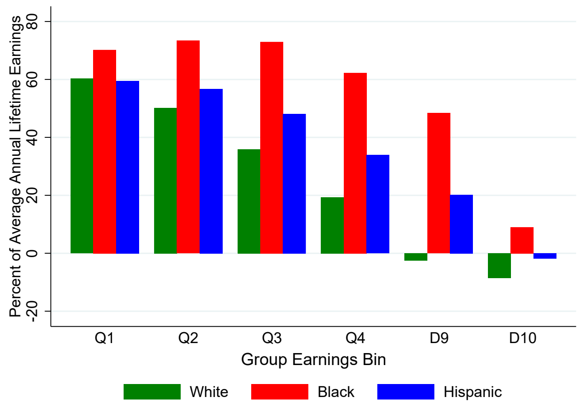
(c) Change in ret. consumption, own race quintiles



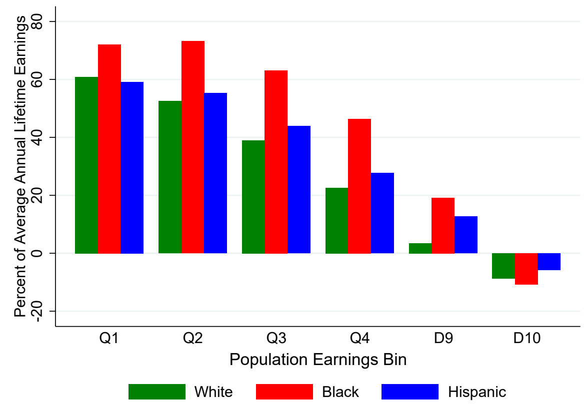
(d) Change in ret. consumption, pop. quintiles

Notes: This figure illustrates the impact of our tax counterfactual exercise on wealth on retirement and consumption in retirement. This counterfactual exercise distributes the aggregate federal tax expenditure so that all workers receive a contribution that is in proportion to their lifetime earnings. We show the effect on two outcomes: the top two panels (A and B) show the change in DC wealth on retirement, with wealth expressed as a proportion of average annual working life earnings. The bottom two panels (C and D) show proportionate change in consumption in retirement (where consumption is the sum of DC wealth and Social Security). For both DC wealth and consumption, we show results by two different types of lifetime earnings bins. The graphs on the left (Panels A and C) form lifetime earnings bins within race. In the graphs on the right (Panels B and D) the bins represent population groups. In each case, lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles.

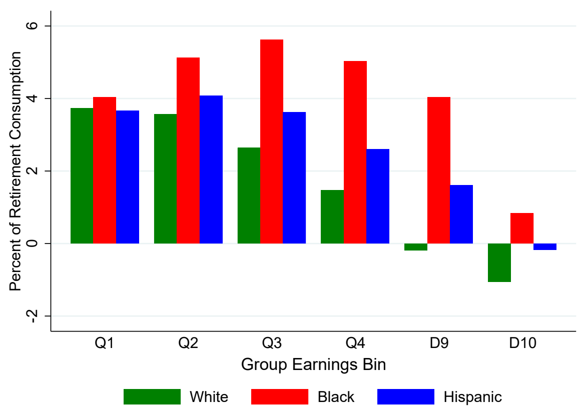
Figure C.27: Change in retirement wealth and consumption under match counterfactual, by race



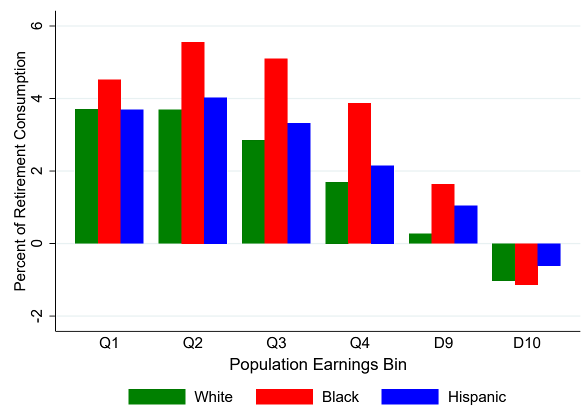
(a) Change in ret. wealth, own race quintiles



(b) Change in ret. wealth, pop. quintiles



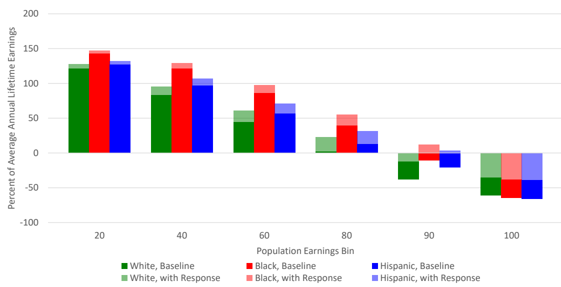
(c) Change in ret. consumption, own race quintiles



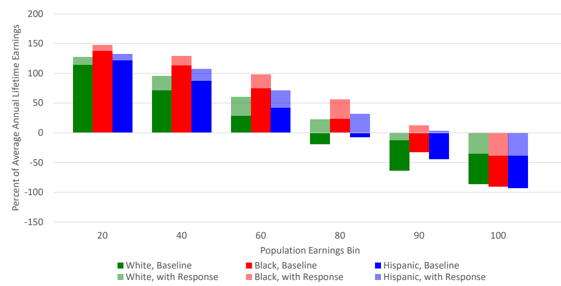
(d) Change in ret. consumption, pop. quintiles

Notes: This figure illustrates the impact of our match counterfactual exercise on wealth on retirement and consumption in retirement. This counterfactual exercise distributes the aggregate employer matches in each firm so that all workers in that firm receive the same proportion of their earnings. We show the effect on two outcomes: the top two panels (A and B) show the change in DC wealth on retirement, with wealth expressed as a proportion of average annual working life earnings. The bottom two panels (C and D) show proportionate change in consumption in retirement (where consumption is the sum of DC wealth and Social Security). For both DC wealth and consumption, we show results by two different types of lifetime earnings bins. The graphs on the left (Panels A and C) form lifetime earnings bins within race. In the graphs on the right (Panels B and D) the bins represent population groups. In each case, lifetime earnings groups are divided into six bins–the bottom four quintiles and the top two deciles.

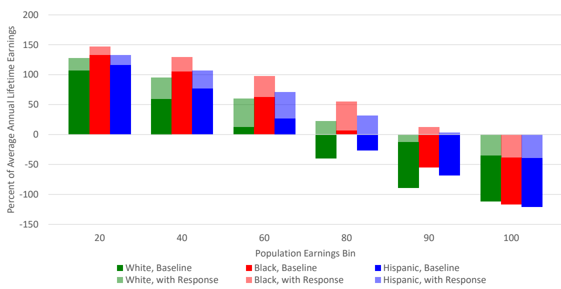
Figure C.28: Change in retirement wealth and consumption with behavioral response, by race and population income bins



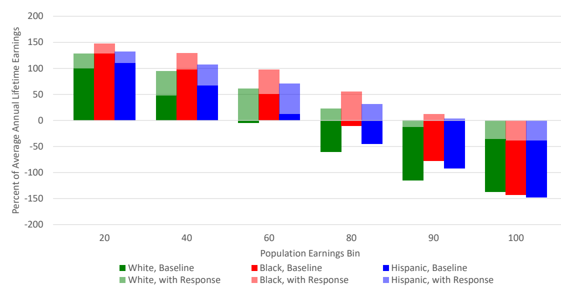
(a) 10c saving effect per dollar of incentives



(b) 20c saving effect per dollar of incentives



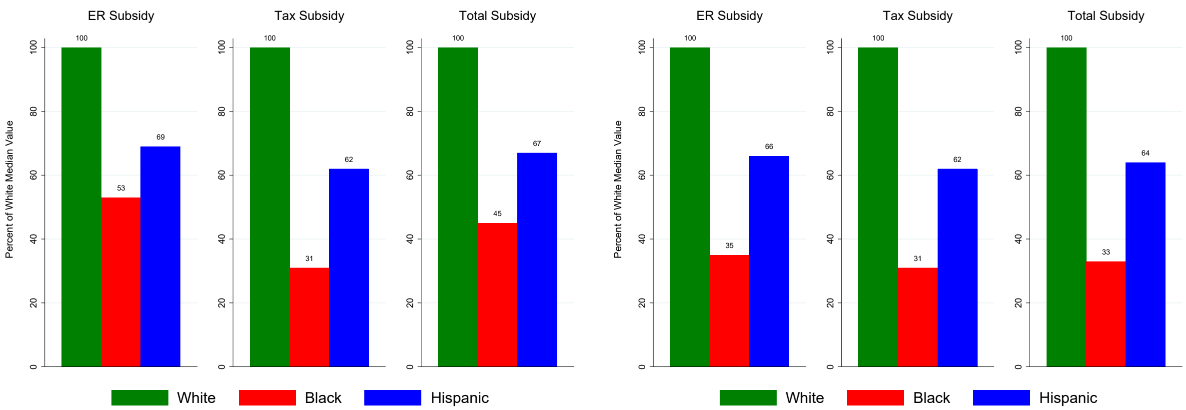
(c) 30c saving effect per dollar of incentives



(d) 40c saving effect per dollar of incentives

Notes: This figure shows alternate versions of Figure 13, Panel B, under different assumptions of behavioral response to a reduction in savings incentives. We assume that if the combined subsidy in baseline is X, then the employee wealth at retirement decreases by $Y\% \cdot X$ under the combined counterfactual, reflecting the loss of savings incentive. Panels A, B, C, and D assume incentive effects of 10%, 20%, 30%, and 40%, respectively. All panels express change in wealth concept at retirement as a percentage of average annual lifetime earnings by race and population lifetime earnings quintiles (with the top quintile split into two deciles). In all panels, the transparent bars show the level of change without behavioral response, while the solid bars show the level of change with the specified incentive effect.

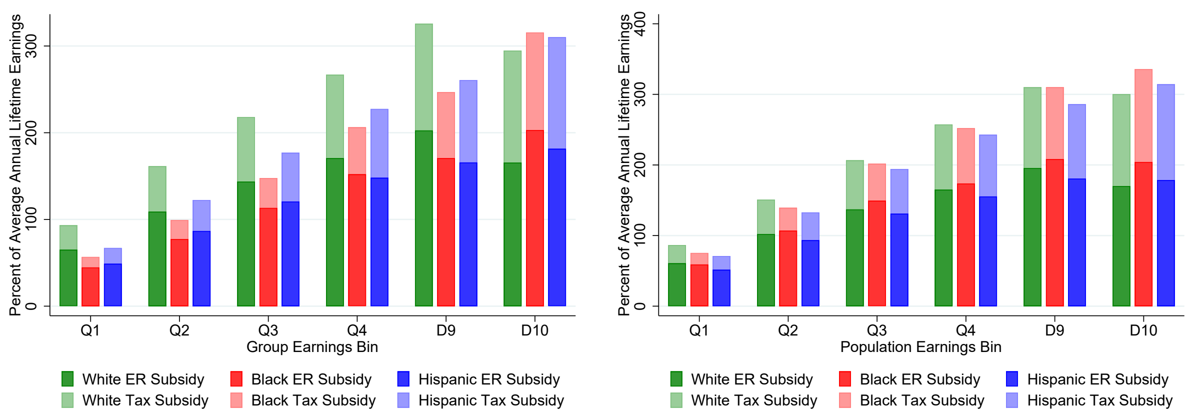
Figure C.29: Median subsidies relative to white under withdrawal assumptions



(a) Subs. rel. to White, withdrawals from EE (b) Subs. rel. to White, withdrawals from EE + ER

Notes: This figure shows employer, tax, and total subsidy to groups relative to a base group under different assumptions relating to early withdrawals. Panel A shows subsidies by race, relative to the White value, under the assumption that all early withdrawals are "deducted" from employee wealth balance. These estimates can be compared to Figure 1, showing a similar measure in the matching sample. By contrast, Panel B employs the assumption used throughout the microsimulation model, that early withdrawals are taken out of both employee and employee wealth balances in a proportional manner.

Figure C.30: Contrib. of employer and tax subsidies to retirement wealth, by race, all withdrawals from EE

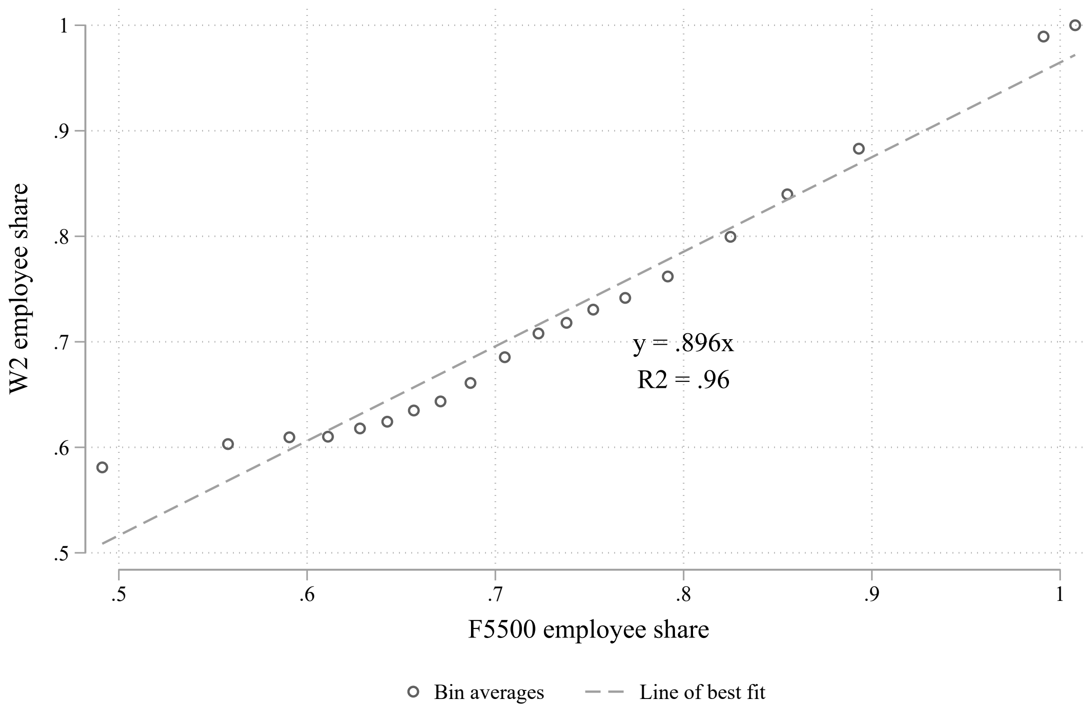


(a) By Own Race Quintiles (b) By Population Quintiles

Notes: This figure is analagous to Figure 11, quantifying the effect of employer matching and tax subsidies on wealth at retirement by race and earnings. It differs from that graph in its treatment of how early withdrawals affect employee and employer shares of wealth at retirement, which are used to calculate the employer match subsidy. In the main model, early withdrawals are taken proportionally out of both the employee and employer wealth balances. In this figure, however, early withdrawals are taken exclusively out of the employee balance. The darker bars are the value at retirement of all employer matches, accounting for any pre-retirement withdrawals. The lighter bars are the value at retirement of the various tax advantages given to DC accounts throughout the life cycle. These amounts are divided by average annual lifetime earnings in order to standardize comparisons across earnings levels. Non-Hispanic White, Black, and Hispanic values are graphed by earnings quintiles, with the top quintile split into two deciles. Panel A has quintiles calculated within each race group, while Panel B's quintiles are calculated across racial groups.

C.4 Supplemental Figures to Appendix A.2

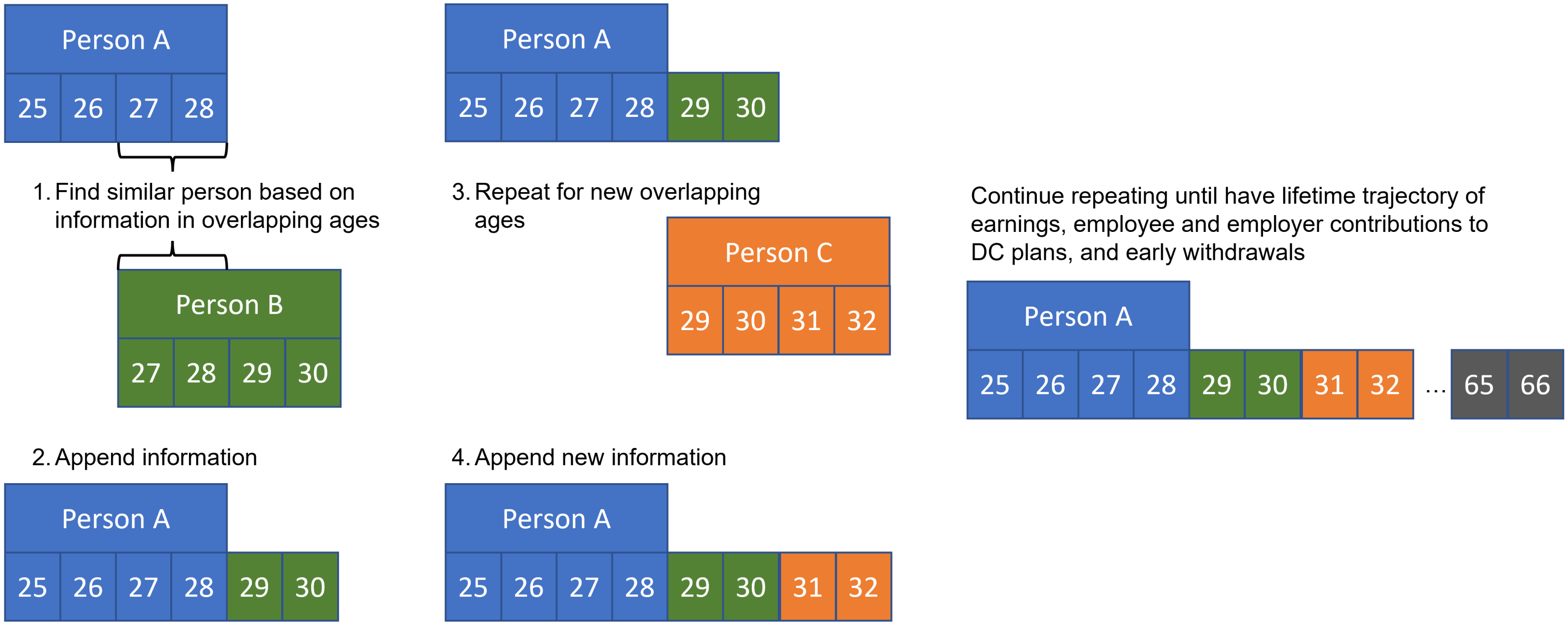
Figure C.31: Bin scatter of W2-imputed vs. Form 5500-reported employee contribution share



This binscatter shows the W2-imputed firm-level employee share of contributions $\left(\frac{total\_employee\_deferred\_compensation}{total\_employee\_deferred\_compensation+total\_employer\_match}\right)$ against the publicly-filed Form 5500 average employee share of contributions.

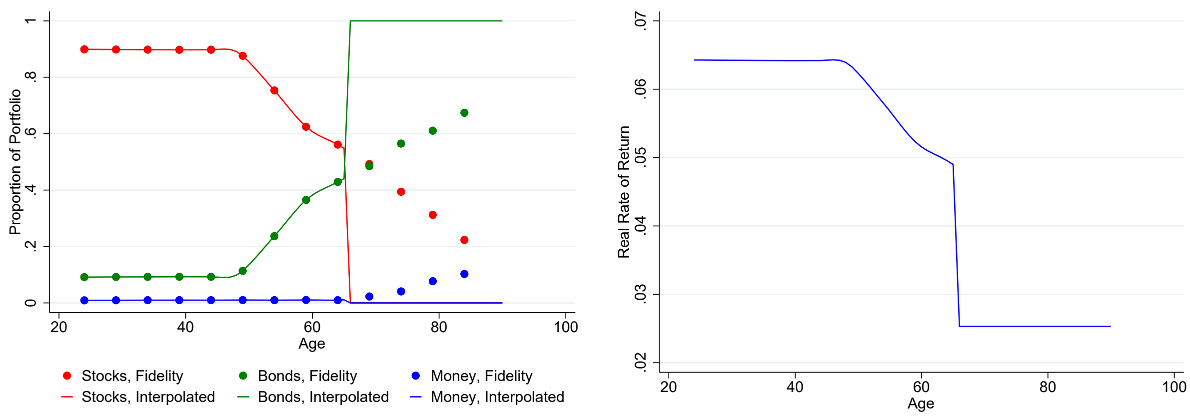
C.5 Supplemental Figures to Appendix B

Figure C.32: Simulating Lifetime Trajectories from Shorter Panels



Notes: This figure shows a schematic of the imputation model used to simulate lifetime trajectories of earnings, deferred compensation, and DC plan withdrawals for workers aged 25 to 65 from the shorter panels available to us for individual workers. We construct full lifetime trajectories by repeatedly matching individuals across overlapping age bins. For example, in 1. Persons A and B have similar earnings and job characteristics in the overlapping ages (27 and 28) so we append Person B's information at 29 and 30 to Person A that adds two additional years to the trajectory of Person A. We repeat this process at increasing ages (31-32, 33-34, ..., 65-66) to create a full lifetime path of earnings, employee and employer contributions to DC plans, and early withdrawals from ages 25 to 65.

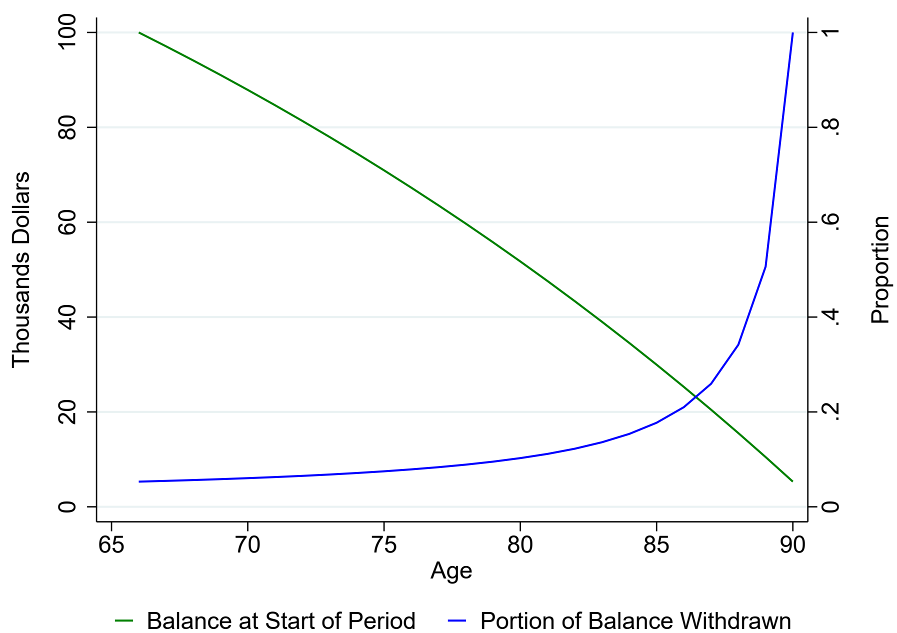
Figure C.33: Portfolio shares and rate of return



(a) Interpolated Portfolio Shares (b) Real Rate of Return over the Lifecycle

Notes: This figure shows underlying parameterizations for portfolio composition and returns in the microsimulation model described in Appendix B. The points of Panel A show actual portfolio shares for Fidelity Freedom Funds for each age. We interpolate shares between these observations for each integer age, given by the lines in Panel A, although we assume exclusive investment in bonds at retirement. Panel B shows the real rate of return, which is determined by the portfolio composition and the associated returns of each component, by age.

Figure C.34: Withdrawal Path



Notes: This figure shows the process for estimating withdrawals in retirement in the microsimulation model described in Appendix B. For the purposes of illustration, we suppose an individual retires with wealth balance of $100,000, which they draw down until their last year of life at age 90. The left axis corresponds to the green line, showing the wealth balance at the start of each period. The right axis corresponds to the blue line, showing the proportion of remaining wealth balance that is withdrawn each period. This process ensures constant withdrawals each period and a smooth draw-down of wealth in retirement.

D Appendix Tables

D.1 Supplemental Tables to Appendix A.2

Table D.1: Summary statistics by sample

Variable	(1) Full, unrestricted	(2) Full (ACS employees)	(3) DC Access (ACS Employees)	(4) DC Access (ACS Employees at Large Firms)	(5) Matching	(6) Parent, Matching
Average age	41.63	41.66	41.81	41.41	41.21	30
Employee contribution ($)	$2,213	$2,248	$2,855	$3,495	$3,351	$1,882
Box 1 W-2 total compensation	$61,140	$61,880	$67,780	$74,330	$72,810	$50,050
Spousal Box 1 W-2 total compensation	$9,915	$9,914	$10,000	$9,931	$9,842	$9,741
Own contrib. (% of inc.)	2.7%	2.7%	3.4%	3.9%	3.8%	2.8%
Own contrib. (% of inc., contrib. >0)	5.9%	5.9%	6%	5.9%	5.8%	4.7%
Positive contrib. dummy (%)	45%	45.6%	57.3%	66.3%	65.2%	59.5%
Match contrib. (% of inc.)					1.9%	1.6%
Own + match contrib. (% of inc.)					5.7%	4.4%
Max match - own contrib. (% of inc.)					1.7%	2%
Positive withdr. dummy	14.3%	14.2%	14.2%	15.7%	16.5%	15.4%
Positive withdr. dummy (withdr. >1000)	11.8%	11.8%	11.8%	13%	13.5%	12%

This table presents from left to right, the progression from our full unrestricted ACS employee sample (before dropping missing control variables), full ACS sample (restricted on nonmissing controls), our full DC access sample, our DC access sample (>100 employees per firm), our matching sample, and our parent-matching sample. This reflects the order of our US population and firm sampling. Spousal income includes spouses claimed on Form 1040 who made $0 in earnings (41% of our matching sample).

Table D.2: Racial and Age Composition by Controls

Control Variable	N	White (%)	Black (%)	Hispanic (%)	Asian (%)	Ages 25-34	Ages 35-44	Ages 45-54	Ages 55-59$\frac{1}{2}$
Panel A: Matching Sample									
Race, year, age, income, education	1753000	71%	11%	12%	6%	28%	28%	31%	13%
Female	1751000	71%	11%	11%	6%	28%	28%	31%	13%
Occupation, county, EIN, tenure	1723000	71%	11%	11%	6%	28%	28%	31%	13%
Family, spousal income, autoenrollment	1722000	71%	11%	11%	6%	28%	28%	31%	13%
Panel B: Parent, Matching Sample									
Race, year, age, income, education	479800	69%	11%	13%	4%	85%	15%		
Female	479700	69%	11%	13%	4%	85%	15%		
Occupation, county, EIN, tenure	471300	70%	11%	13%	4%	85%	15%		
Family, spousal income, parent income	471200	70%	11%	13%	4%	85%	15%		
Parent awareness	447500	70%	11%	13%	4%	86%	14%		

Notes: This table presents the racial and age composition of our matching and parent-matching samples as we drop controls.

Table D.3: Change in DC wealth at retirement under the counterfactual tax policy

Panel A: Quintiles (Q) & deciles (D) of the **race-specific** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Absolute change in DC Wealth ($'000)	White	+10.5	+12.8	+9.3	+0.1	-25.2	-68.6
	Black	+9.1	+14.7	+17.4	+16.4	+11.1	-15.9
	Hispanic	+11	+14.9	+13.9	+8.3	+1.0	-43.7
Relative change in the racial DC wealth gap	B-W Gap	-20.8%	-15.3%	-11.6%	-7.4%	-4.6%	-3.1%
	H-W Gap	-29.1%	-17.7%	-11.7%	-6.5%	-6.3%	-2.6%
Relative change in the racial consumption gap	B-W Gap	-1.8%	-4.5%	-5.4%	-4.8%	-4.7%	-4.4%
	H-W Gap	-6.5%	-6.1%	-5.6%	-4.4%	-6.4%	-4.0%

Panel B: Quintiles (Q) & deciles (D) of the **population** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Absolute change in DC Wealth ($'000)	White	+10.2	+12.9	+10.5	+2.3	-15.3	-65.3
	Black	+11.1	+17	+16.8	+10.1	-4.5	-52.9
	Hispanic	+11.3	+15.0	+12.7	+5.1	-7.6	-64.8
Relative change in the racial DC wealth gap	B-W Gap	-33.5%	-25.3%	-17.1%	-9.6%	-7.3%	+0.2%
	H-W Gap	-40.6%	-24.9%	-15.4%	-9.5%	-13.8%	+6.2%
Relative change in the racial consumption gap	B-W Gap	-9.4%	-14.4%	-12.1%	-8.7%	-8.5%	-2.1%
	H-W Gap	-64.3%	-13.2%	-9.8%	-8.3%	-14.5%	+3.5%

Notes: This table shows the effect of the tax counterfactual on wealth at retirement by race and income bin, as well as the corresponding effect on the wealth gaps between White and Black/Hispanic savers. Changes are given by group-specific (Panel A) and population (Panel B) income quintiles, with the top quintile split into two deciles.

Table D.4: Change in DC wealth at retirement under the counterfactual employer contribution policy

Panel A: Quintiles (Q) & deciles (D) of the **race-specific** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Absolute change in	White	+9.3	+14.6	+15.1	+12	-2.3	-18.0
DC Wealth ($'000)	Black	+7.6	+14.5	+20.4	+24.2	+26.2	+8.9
	Hispanic	+8.4	+13.9	+16.6	+16.5	+14.1	-2.4
Relative change in the	B-W Gap	-17.2%	-13.9%	-12.2%	-9%	-6.3%	-3.2%
racial DC wealth gap	H-W Gap	-17.7%	-12.5%	-10.2%	-7.1%	-6.0%	-3.9%
Relative change in the	B-W Gap	-0.9%	-3.4%	-5.1%	-5.0%	-5.1%	-3.2%
racial consumption gap	H-W Gap	+0.7%	-2.5%	-3.9%	-3.8%	-5.0%	-3.9%

Panel B: Quintiles (Q) & deciles (D) of the **population** income distribution

		Q1	Q2	Q3	Q4	D9	D10
Absolute change in	White	+8.8	+14.1	+15.2	+12.9	+3.0	-17.0
DC Wealth ($'000)	Black	+9.9	+19.3	+24.1	+25.8	+16.1	-16.3
	Hispanic	+8.7	+14.6	+16.8	+15.6	+10.9	-9.6
Relative change in the	B-W Gap	-32.8%	-29.2%	-23.7%	-18.4%	-12.6%	1.4%
racial DC wealth gap	H-W Gap	-23.9%	-17.5%	-15.5%	-12.5%	-17.2%	-8.8%
Relative change in the	B-W Gap	-10.6%	-17.7%	-17.0%	-15.3%	-12.1%	+0.7%
racial consumption gap	H-W Gap	+0.7%	-5.6%	-8.4%	-9.3%	-16.4%	-8.4%

Notes: This table shows the effect of the employer-match counterfactual on wealth at retirement by race and income bin, as well as the corresponding effect on the wealth gaps between White and Black/Hispanic savers. Changes are given by group-specific (Panel A) and population (Panel B) income quintiles, with the top quintile split into two deciles.

D.2 Supplemental Table to Appendix B

Table D.5: Parameter and Variable Definitions

Earnings, Consumption, Social Security		**State Variables**	
$e_{i,t}$	Earnings	i	Individual
α	Discount rate in retirement	$t \in \{25, \ldots, 90\}$	Age
c_t^j	Consumption in retirement	$j \in \{DC, BK\}$	Type of savings vehicle
$aime_i$	Average indexed monthly earnings		
e^{max}	Social Security taxable maximum		**Taxes**
δ_1	First PIA bend point	$T(\cdot\ ,\ \cdot\ ,\ \cdot)$	Federal income tax function
δ_2	Second PIA bend point	$\tau_{i,t}^{e,j}$	Taxes owed on earnings
$ss_{i,t}$	Annual Social Security benefits	$\tau_{i,t}^{ss,j}$	Taxes owed on Social Security Benefits
		$\tau_{i,t}^{c,j}$	Taxes owed on savings
	Wealth Flows	$\tau_{i,t}^{r,j}$	Taxes owed on returns
$dc_{i,t}^{ee}$	Employee savings	$\tau_{i,t}^{w,j}$	Taxes owed on withdrawals
$dc_{i,t}^{er}$	Employer savings	$\hat{\tau}_{i,t}^{r,j}$	Hypothetical taxes owed on returns
$w_{i,t}^j$	Savings account withdrawals		
$f_{i,t}^j$	Flow into retirement account		**Lifetime Measures**
$B_{i,t}^j$	Wealth balance	$A_{i,t}^{DC}$	DC Wealth
$B_{i,t}^{p,j}$	Principal part of wealth balance	$SS_{i,t}$	Social Security Wealth
$B_{i,t}^{g,j}$	LTCG part of wealth balance	$C_{i,t}$	Consumption
$w_{i,t}^{k,j}$	LTCG portion of withdrawal	$C_{i,t}^{BK+SS}$	Consumption brokerage WC
		A_i^T	DC tax subsidy
	Rate of Return	DC_i^{EE}	Value of employee contributions
ρ_t	Rate of return at age t	DC_i^{ER}	Value of employer contributions
$r_{i,t}^{g,j}$	Return from unrealized capital gain	A_i^{EE}	Wealth attributable to employee
$r_{i,t}^{k,j}$	Return from LTCG distributions	A_i^{ER}	Employer subsidy
$r_{i,t}^{i,j}$	Return from interest distributions	LE_i	Value of lifetime income
s_t^k	Portion of assets invested in stocks		
s_t^b	Portion of assets invested in bonds		**Counterfactuals**
s_t^m	Portion of assets invested in money	$C_i'^T$	Counterfactual tax subsidy
ρ^k	Real rate of return on stocks	$A_i'^{DC}$	DC Wealth under tax CF
ρ^b	Real rate of return on bonds	$C_i'^{DC}$	Consumption under tax CF
ρ^m	Real rate of return on money	dc^*	Counterfactual employer match
χ^g	Share from unrealized capital gain	$A_{i,t}^{*DC}$	DC wealth under ER CF
χ^k	Share from LTCG distributions	$C_{i,t}^{*DC+SS}$	Consumption under ER CF
χ^i	Share from interest distributions	$A_{i,t}^{\dagger DC}$	DC Wealth under combined (CB) CF
$\hat{r}_{i,t}$	Implied post-tax rate of return	$C_{i,t}^{\dagger}$	Consumption under CB CF

Table D.6: Parameters Values and Sources

Parameter	**Value**	**Source**
e^{max}	\$128,400	Social Security Administration (2023b)
δ_1	\$895	Social Security Administration (2023a)
δ_2	\$5,397	Social Security Administration (2023a)
ρ^k	0.0688	Jordà et al. (2019)
ρ^b	0.0253	Jordà et al. (2019)
ρ^m	0.0103	Jordà et al. (2019)
σ_t^k, σ_t^b, σ_t^m	Figure C.33a	Fidelity (2023)
χ^g	0.5	Yahoo Finance, Sialm and Zhang (2020)
χ^k	0.4	Yahoo Finance, Sialm and Zhang (2020)
χ^i	0.1	Yahoo Finance, Sialm and Zhang (2020)