The Family as Insurer: Race, Long-Term Care, and Wealth After Retirement

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Abstract

I study how differences in family-care arrangements contribute to racial differences in wealth after retirement. Using Health and Retirement Study data, I estimate a saving model of White and Black single women aged 70 or older, distinguishing groups receiving little, moderate, or intensive family care. In this sample, Black retirees' median wealth is about one fifth of White retirees', and a large gap persists through old age. Retirees in the intensive-care group receive more help, face a lower probability of a nursing-home bill, hold less wealth, and leave estates less often. Most of the simulated wealth gap at ages 74 to 84 reflects differences in starting wealth and income. Differences in the shares of women in these groups account for 11 to 19 percent of the gap in dollars. The comparison includes the groups' differences in care hours, nursing-home risk, the weight the model puts on bequests, and starting resources. I then evaluate a subsidy covering half of nursing-home bills, available regardless of wealth. For retirees in the middle third of each race's income distribution, the subsidy provides the same welfare gain as a one-time payment averaging $92,000 for White retirees and $13,000 for Black retirees, in 2018 dollars. For women with few resources, part of the subsidy can take the place of support the model already provides.

JEL codes: D14, D15, I14, J14, J15.

Keywords: retirement saving, racial wealth gap, long-term care, informal care, health.

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1 Introduction

The racial wealth gap remains large among older single women. Retirees bring different resources into old age and face uncertain medical bills, care needs, and lifespans. Help from relatives and means-tested public insurance can reduce the expenses they pay themselves. I study how starting resources, family care, and long-term-care risks contribute to wealth differences after retirement. I then examine what these differences imply for the gains from a subsidy for nursing-home expenses.

I study White and Black single women aged 70 or older using the Health and Retirement Study (HRS), from 1996 to 2018. I focus on women because they make up most single retirees at these ages. Studying singles lets me examine family care and saving without modeling a couple's joint decisions or spousal care.

Wealth includes financial assets, real estate other than the primary residence, vehicles, and business equity, net of debt. Black retirees hold about one fifth of White median wealth and receive roughly twice the family-care hours within their respective income groups. Intensive-care families are twice as common among Black retirees. White retirees buy more paid care and leave estates more often. Black retirees have shorter expected lifespans and are more likely to receive Medicaid.

I estimate a retirement-saving model for these women following De Nardi, French, and Jones (2010) and Bueren (2023). Retirees choose consumption, paid care, and saving while facing uncertain health, medical bills, and lifespans. I group retirees by their histories of family care. Each group has its observed care hours and its own probability of a nursing-home expense. Those receiving intensive family care get more help and report nursing-home use less often. I represent that use by a possible bill. Public transfers provide minimum consumption and paid care when a woman's resources are insufficient.

To account for the wealth gap, I replace White starting resources, care arrangements, and risk profiles with their Black counterparts. I calculate median wealth at each age from 74 to 84 and average those dollar amounts. Women enter the simulation at their observed starting ages, which can be older than 70.[1]

Starting wealth and income account for 65 to 90 percent of the simulated wealth gap. Changing the shares of women who receive little, moderate, or intensive family help accounts for 11 to 19 percent. The groups also differ in their chances of a nursing-home bill, their starting resources, and the weight the model puts on leaving an estate.[2]

[1] I average each input's contribution across all orders in which the inputs can change. Section 5 and Appendix H describe the decompositions.

[2] A separate decomposition attributes less than two percent of the gap to replacing White care hours with Black care hours within each group.

The wealth and estate patterns help explain why the care groups matter. Retirees receiving intensive family care get more unpaid help, face a lower chance of a nursing-home bill, and hold less wealth. They also leave estates less often, which the model matches with a lower weight on financial bequests. Retirees receiving moderate care hold more wealth than those receiving little care, so hours alone do not explain the ordering.

I next value one part of the protection associated with intensive family care. I give retirees receiving little or moderate family care the intensive type's lower probability of a nursing-home bill, within race, age, and health. I calculate the hypothetical one-time payment that would make a retiree as well off under the original arrangement as with this lower probability. In the middle third of each race's income distribution, the average value for retirees with little family care is \$131,000 for White retirees and \$30,000 for Black retirees, in 2018 dollars.

The policy experiment pays half of the modeled nursing-home bill whenever it occurs. The subsidy is available regardless of wealth, so retirees do not have to spend down their savings to receive it. In the middle income third, the subsidy is worth \$92,000 for White retirees and \$13,000 for Black retirees. In the model, the subsidy saves money for women who would otherwise pay the bill themselves. For women who would rely on means-tested support, it can replace some of that support. The comparison also reflects differences in family arrangements, starting resources, nursing-home risks, and fitted preferences. I report full coverage as a benchmark.[3]

The paper contributes to research on wealth and saving late in life. Medical expenses, longevity, and bequests help explain why retirees retain wealth (De Nardi, French, and Jones, 2010; Kopecky and Koreshkova, 2014; Lockwood, 2018; Ameriks, Briggs, Caplin, Shapiro, and Tonetti, 2020). Life-cycle studies also examine racial differences in wealth and health (Aliprantis, Carroll, and Young, 2019; Foltyn and Olsson, 2025). I ask how much of the wealth gap in old age reflects the wealth and income women have at sample entry and how much reflects differences in the shares receiving little, moderate, or intensive family help.

I also study how family care and public insurance affect saving and policy gains. Family support affects saving and the value of care policies (Barczyk and Kredler, 2018; Bueren, 2023; Mommaerts, 2025). Existing public coverage affects the gains from additional insurance (Brown and Finkelstein, 2008; De Nardi, French, and Jones, 2016). I compare these outcomes across White and Black retirees with different resources and care arrangements,

[3]In the probability experiment, the bill, care hours, and bequest preferences stay fixed. In the subsidy experiment, family-care hours and bill probabilities remain fixed. The probability experiment values a specified reduction in expense risk, rather than all family care. These values allow consumption, paid care, saving, and bequests to adjust over each retiree's remaining life. Program costs are gross payments, before deducting any reduction in existing Medicaid spending. The calculations exclude caregivers' welfare and the cost of financing. Section 6 gives the full definitions.

complementing earlier work on racial differences in long-term-care policy (Wallace, Levy-Storms, Andersen, and Kington, 1997).

The data bring together care, nursing-home use, wealth, estates, medical spending near death, and Medicaid receipt for the same retirees. These comparisons complement evidence on caregiving networks (Favreault, Dey, Marton, Lamont, and Anderson, 2023), nursing-home segregation (Smith, Feng, Fennell, Zinn, and Mor, 2007), and inheritance differences (Menchik and Jianakoplos, 1997; Avery and Rendall, 2002). Earlier differences, including those associated with marital histories, enter the model through retirees' starting resources and circumstances.

The paper is organized as follows. Section 2 describes the data and presents seven facts. Section 3 presents the model, and Section 4 describes estimation. Section 5 reports fit, decomposes the wealth gap, and examines family types and the fit to Black data. Section 6 values a lower chance of a nursing-home bill and evaluates a subsidy covering half of nursing-home expenses. Section 7 concludes. Appendix H reports the alternative decomposition, floor sensitivity, and cash-payment experiment.

2 Data and descriptive facts

Seven facts describe wealth, care, and risks among older singles. Wealth and Medicaid receipt are measured for women; some care and estate comparisons use both women and men. Facts 1 and 5 describe wealth and estates. Facts 2 and 4 describe family care and its relationship with nursing-home use. Fact 3 describes health and life expectancy. Facts 6 and 7 describe medical spending and Medicaid receipt. These descriptive comparisons guide the model.

2.1 Sample and definitions

I use the HRS from 1996 to 2018 and select single (non-married, non-partnered) retirees aged 70 and older, whom I follow until death. The HRS records wealth, income, health, mortality, out-of-pocket medical spending, and, through its care modules, the hours of help received with daily activities and the identity of each helper. The saving model compares non-Hispanic White and non-Hispanic Black single women. The estimates, wealth decompositions, and policy valuations all concern these women. In the model and results, "retirees" refers to older single women. Some descriptive comparisons and first-stage inputs also use single men; I identify these broader samples below and in the appendices.

Wealth. I measure wealth as financial assets, real estate other than the primary residence, vehicles, and business equity, net of debt. The measure excludes primary-residence equity. I use these assets as the resources available to retirees in the model. Appendix A gives the data definitions.

Health and care needs. I use the HRS measures of activities of daily living (ADL) and instrumental activities of daily living (IADL), such as bathing, dressing, walking, shopping, and managing money. A respondent is in *good health* with no limitations, in *bad health* with any IADL limitation or up to two ADL limitations, and *impaired* with more ADL limitations or severe disability. Bad and impaired health indicate increasing care needs. I use these groups to estimate survival, health transitions, and medical spending.

Formal and informal care. Care is classified by the identity of the caregiver. *Informal care* is unpaid help from relatives or friends; *formal care* is paid professional assistance (home health aides, nursing services, and similar).

Permanent income. As in De Nardi, French, and Jones (2010), I rank retirees by income from Social Security and defined-benefit pensions, adjusted for age and gender.[4] I divide each race's permanent-income distribution into thirds and refer to these groups as income terciles. Tables label them T1 (lowest), T2 (middle), and T3 (highest).

2.2 Fact 1: a large wealth gap persists through old age

Figure 1 shows median assets by age and permanent-income tercile for White and Black single women in the first HRS cohort. Black median wealth is roughly one fifth of White median wealth, and the gap persists at older ages. The later cohort shows a similar pattern. Each age describes the surviving respondents.[5] Section 5 examines how the model accounts for these wealth differences.

Wealth in old age reflects both what retirees brought into retirement and what they have spent since then. A large gap at older ages need not mean that the groups respond differently to care needs. It may persist because they began with different resources. I use the observed wealth profiles to define the gap that the model will account for, and the care, estate, and receipt patterns below to describe the circumstances in which retirees make their spending decisions.

[4] The measure is the household fixed effect from a regression of annuitized income on age and gender. Appendix A gives the construction.

[5] The figure compares age-specific medians; it does not follow a fixed group or measure individual saving rates.

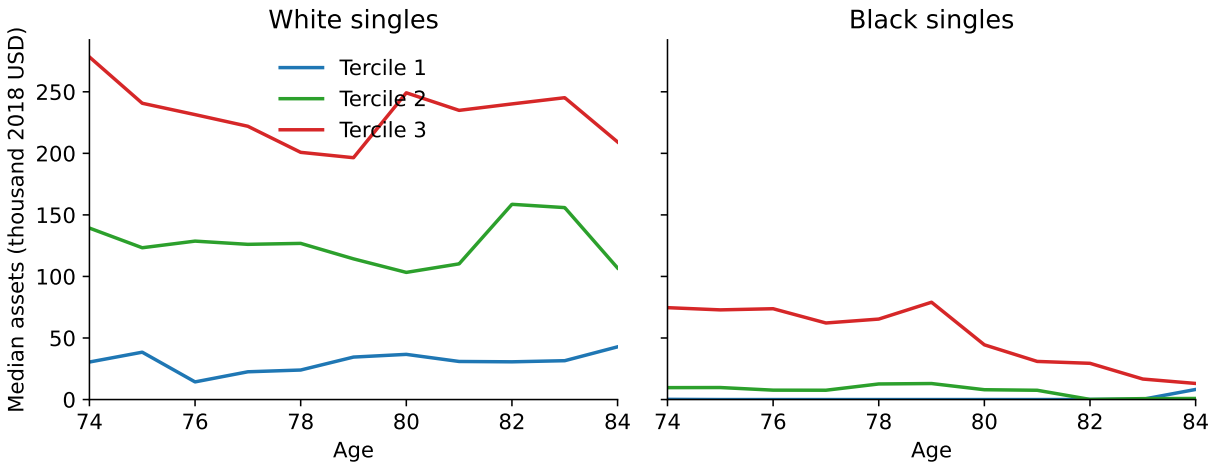


Figure 1: Median assets by age and permanent-income tercile, single women, HRS cohort 1 (2018 dollars). Left: White singles. Right: Black singles.

2.3 Fact 2: Black retirees receive much more family care; White retirees buy more market care

Figure 2 shows daily hours of family and paid care among retirees with impaired health, by race and permanent-income tercile. Black retirees receive roughly twice as many family-care hours within their respective terciles. White retirees buy more paid care, and paid hours rise with income rank.[6]

The care comparison describes an important difference in how daily needs are met. Unpaid help supplies services that would otherwise have to come from paid providers or go unmet. It can therefore matter to a retiree even when it does not appear as income or spending. Looking at paid care alone would miss much of the help received by Black retirees. I use both sources of care when describing the support available to each group.

2.4 Fact 3: worse health and shorter lives among Black retirees

Table 1 reports remaining life expectancy at age 70 from the estimated health and mortality transitions (Section 4). Black retirees have shorter expected lives in every gender, income, and health group shown. A healthy Black woman at median permanent income who reaches 70 can expect another 12.8 years, compared with 14.4 for a White woman. Averaging over health states, the difference is about 2.6 years for women and 1.7 for men. Black retirees also spend a larger share of their remaining lives needing care. Greater care needs can increase

[6]Income terciles are defined separately by race. The comparison is at similar income ranks, rather than the same income.

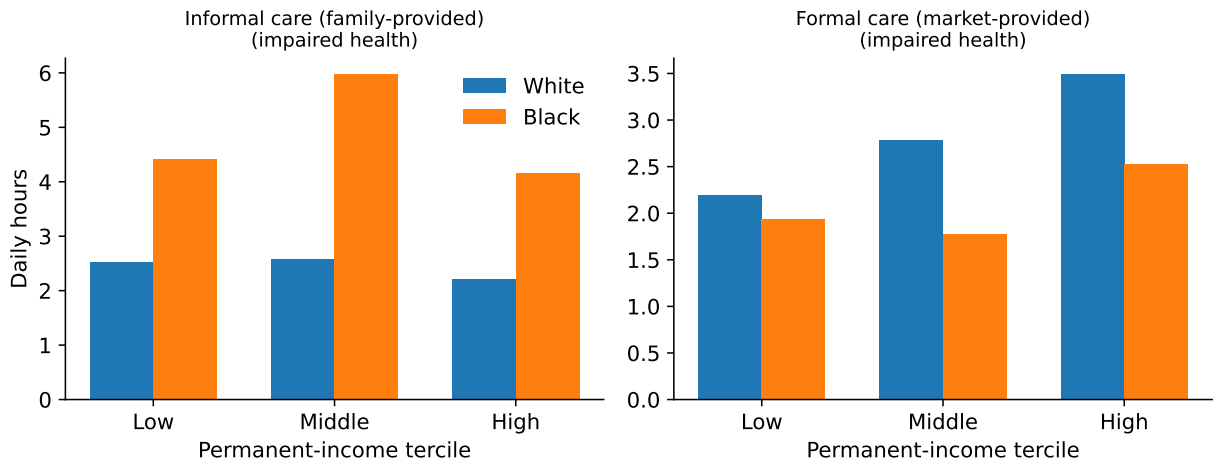


Figure 2: Daily hours of care among impaired single retirees, by race and permanent-income tercile. Left: informal (family-provided) care. Right: formal (market-provided) care. HRS 1996–2018.

saving, while shorter lives reduce the time over which resources are needed. The model measures the combined effect.

2.5 Fact 4: care histories group retirees with different resources and risks

I group retirees by how much family care they receive when they need help. Following Bueren (2023), I use their complete care histories to identify three groups: *none*, *moderate*, and *intensive* care (Figure 3). In impaired health, they receive minutes, one to two hours, and up to ten hours of help per day, respectively. The label "none" denotes little care. Appendix E describes the statistical classification.

Intensive-care types account for 23 percent of Black and 11 percent of White single women entering the sample in 1996. Conditional on the broad health categories used here, retirees receiving little family care are roughly twice as likely to report a nursing-home episode as intensive-care types.

Among White single decedents, pooling women and men, intensive-care types are less likely to leave an estate above $1,000: 57 percent do so, compared with 61 percent of the other groups. The none and moderate groups have similar shares, 61.0 and 60.4 percent. I therefore use one bequest weight for those two groups and a separate weight for the intensive group.

Retirees receiving intensive family care also hold less wealth within each income tercile.

Table 1: Life expectancy in years, conditional on reaching age 70

		Men			Women		
	PI percentile	Impaired	Bad	Good	Impaired	Bad	Good
White	10	4.8	5.9	6.8	8.7	10.3	11.3
	50	6.0	7.5	8.6	11.4	13.4	14.4
	90	5.4	7.1	8.3	10.8	13.1	14.2
	all PI, all health		8.2			13.4	
Black	10	4.6	5.4	6.0	8.4	9.4	10.1
	50	5.9	6.8	7.6	10.8	12.0	12.8
	90	5.2	6.2	7.1	9.9	11.2	12.1
	all PI, all health		6.5			10.8	

Notes: Implied by health/mortality transition probabilities estimated from the HRS 1996–2018 (multinomial logit on age, gender, permanent income, previous health, and interactions), by race.

At the top tercile, their median assets are roughly $172,000, compared with $241,000 for those receiving little care and $281,000 for moderate care.[7]

The care histories connect family help to the other outcomes that the model must explain. Retirees receiving intensive care differ in their wealth, estate outcomes, and nursing-home use as well as in their hours of help. I preserve these group differences when constructing the model. This makes it possible to ask how the prevalence of different care arrangements contributes to the wealth gap, and then to examine a particular source of protection within those arrangements.

2.6 Fact 5: White retirees leave estates more often

The HRS exit interviews record estates left at death. Among single retirees, pooling women and men, 61 percent of White decedents leave more than $1,000, compared with 36 percent of Black decedents. Among those leaving an estate, the median is $118,000 for White and $71,000 for Black decedents. The difference also appears within family types, so their different proportions alone cannot explain it. These patterns complement evidence on racial differences in inheritance receipt (Menchik and Jianakoplos, 1997; Avery and Rendall, 2002). I use these pooled estate shares as targets for the saving model of single women, alongside wealth and care outcomes.

The estate observations add information that wealth while alive cannot provide. A retiree may retain savings to pay for future care, to leave money to heirs, or for both reasons. If

[7]Family help may reduce saving needs, while fewer resources may increase reliance on relatives. The comparison combines these possibilities. The model takes the observed care arrangements as given.

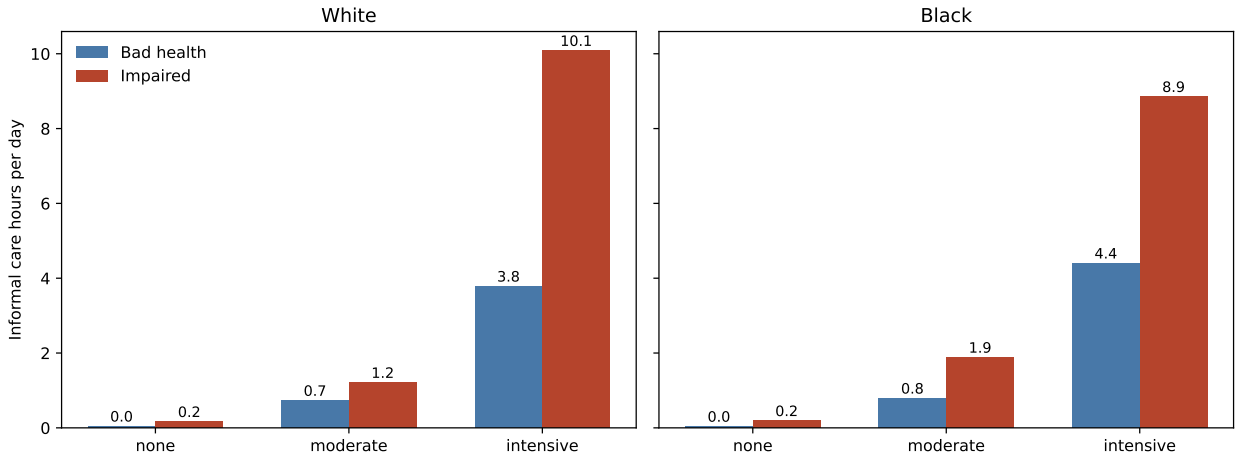


Figure 3: Informal care hours per day in the care-need states, by family type and race. Types (none / moderate / intensive) from an EM finite-mixture classification of care histories. HRS 1996–2018, single retirees 70+.

she dies before spending those savings, an estate can remain even when leaving one was not her main purpose. I therefore fit estate shares together with wealth and care use. The joint fit helps the model describe how resources are used during life and what remains at death.

2.7 Fact 6: medical spending near death differs; death expenses are similar

The exit interviews for single women and men report out-of-pocket medical spending since the last core interview and expenses associated with death. Rescaling medical spending by months alive gives an annualized median of $2,267 for White and $527 for Black single decedents aged 70 and over, in 2018 dollars. Funeral and legal expenses are similar: medians of $10,463 and $10,265.

Lower out-of-pocket spending can reflect insurance coverage and differences in care use.[8]

2.8 Fact 7: Black retirees receive Medicaid more often, including without care limitations

Table 2 compares Medicaid receipt by health and income. Among retirees needing care, Black receipt is about two to three times White receipt within each race's income terciles.

[8]Lower out-of-pocket medical spending may reflect differences in who pays, how much care people use, which services they receive, or their insurance. The exit interviews do not separate these explanations. To calibrate the model's estate deduction m_D, I add the separately calculated medians of medical spending and death expenses. This gives $12,730 for White and $10,793 for Black decedents. The sum of these medians differs from the median of each person's total expenses. Appendix B, B.6, describes the calculation.

Table 2: Medicaid receipt by health, race, and income tercile

	Tercile	White	Black	Ratio
Healthy	1	0.153	0.568	3.7
	2	0.023	0.279	12.4
	3	0.003	0.048	16.8
Care-need	1	0.385	0.717	1.9
	2	0.126	0.403	3.2
	3	0.052	0.144	2.8

Notes: Share of person-years with means-tested (Medicaid) receipt, HRS single women 70 and over, by ADL/IADL health and within-race income tercile. All six racial differences are significant in a two-sample test using the person-block bootstrap standard errors ($t = 6.5$, 4.7 and 2.4 for the healthy rows; 8.4, 6.7 and 3.7 for the care-need rows). Terciles are cut within race; the text reports the same comparison at common pooled income (healthy-row ratios 2.6, 4.7 and 4.9) and with income controls. Section 5 says which of these cells enter the structural estimation.

Among those without ADL/IADL limitations, it is about four to seventeen times as high. Retirees without these limitations can still have medical expenses (Appendix B). Receipt alone does not show how they qualified.

The receipt gap remains when I use common income groups for both races. Appendix A reports the comparisons.

After controlling for income, age, and wave, Black Medicaid receipt is 12.8 percentage points higher among retirees without care limitations, compared with a White receipt rate of 4.7 percent. Among those needing care, the difference is 10.0 points, compared with a White rate of 19.5 percent.[9] The proportional gap remains larger among retirees without care limitations.

The same means-tested rules can produce different receipt rates when groups have different resources. Eligibility and enrollment also affect who receives support.[10] Information, application costs, and stigma can affect enrollment (Moffitt, 1983; McGarry, 1996). Fact 7 describes receipt under these common rules.

These receipt patterns matter for the financial risk of care. A medical bill of the same size can reduce one retiree's own resources while drawing mainly on public support for another. Wealth and care expenses alone therefore do not reveal how much additional protection a

[9] I use a linear probability model with income-decile controls and standard errors clustered by person. For the first comparison, $t = 5.1$. The controls exclude countable assets and eligibility. The files have no geographic identifier, so the estimates pool states and regions.

[10] Medicaid covers some people through SSI-related eligibility and others through medically-needy provisions. The latter allow qualifying medical expenses to offset excess countable income while retaining resource requirements. The table does not distinguish these routes or measure take-up among eligible people.

policy would provide. The receipt data help the model describe the public support already available when a retiree faces an expense.

The facts describe Black retirees with lower measured wealth, more informal care, shorter expected horizons, and higher Medicaid receipt. White retirees hold more wealth and purchase more market care. The model asks how those starting positions, risks, and care arrangements contribute to wealth differences after retirement. It then measures their implications for the gains from public support.

3 Model

I use an annual saving model of single women aged 70 to 100, following De Nardi, French, and Jones (2010) and Bueren (2023). Retirees choose consumption, paid care, and saving while facing uncertain health, lifespans, and medical expenses. They differ in permanent-income rank PI, health, assets, a persistent medical-expense shock, and family type. Simulations begin at each retiree's observed age in the 1996 sample. I use the model to account for wealth differences and to evaluate public support.

Health and care needs. Health h_t is healthy, bad, impaired, or deceased. Bad and impaired health indicate increasing care needs. Annual transitions depend on age, income, gender, and race and are estimated from the HRS. I use the ADL/IADL classification described above.

Family type. Each retiree has a fixed care type $F \in \{\text{none}, \text{moderate}, \text{intensive}\}$. Her type determines the family-care hours $l_{IC}(h, F)$ she receives and her probability of a nursing-home bill. I estimate the two schedules from care histories. Intensive-care retirees receive more help and report nursing-home use less often. The bequest weight $\theta(F)$ also varies by type: none and moderate types share θ_{rest}, while intensive types have θ_{int}. This grouping follows their estate patterns.

I infer each retiree's type from her observed care history and keep it fixed during the simulation. She takes the family's care hours as given and chooses consumption, paid care, and saving.[11]

[11] Family hours do not respond to prices, transfers, or wealth. Nursing-home probabilities are estimated separately, so an extra care hour does not automatically change them. The welfare measure covers the retiree and excludes caregivers' time and forgone earnings.

Preferences. Period utility over consumption c and purchased formal care l_{FC} is

$$u(c, l_{FC}; h, l_{IC}) = \frac{c^{1-\sigma}}{1-\sigma} + \alpha(h) \frac{\left[l_{FC} + \omega\, l_{IC}\right]^{1-\nu}}{1-\nu}, \tag{1}$$

with family-care weight ω and $\alpha(\text{healthy}) = 0$. Care utility applies in the care-need states. At death, I deduct the calibrated expense m_D from assets to obtain the estate $b = \max\{a' - m_D, 0\}$, valued as

$$\theta(F) \frac{(b+\kappa)^{1-\sigma}}{1-\sigma}, \tag{2}$$

where κ governs how bequest utility varies with estate size (Lockwood, 2018). The type-specific weights summarize the observed estate patterns.[12]

The retiree balances spending today against the uses of wealth later in life. Buying more care can improve life when she needs help, but leaves less for consumption or saving. Keeping assets gives her resources for future bills and for a possible estate. Family help changes this choice by contributing to care without requiring a purchase. Its value depends on how much help she already receives, how costly it would be to replace, and how she values care relative to consumption and bequests.

A possible large bill gives saving an additional role. A retiree with sufficient resources may use assets to absorb the expense. One with few resources relies more heavily on the public guarantee. This difference allows the model to connect the wealth comparisons to the policy analysis: the same reduction in a bill can protect quite different amounts of private spending across retirees.

Medical and nursing-home bills. Ordinary out-of-pocket medical spending varies with age, health, income, gender, and race and can remain high across years (French and Jones, 2004). I add a separate bill to represent nursing-home use. In each year with care needs, the retiree faces a chance $\pi_{NH}(t, h, F)$ of receiving this bill. The probability depends on age, health, race, and family type and is estimated from reported nursing-home use. The bill has the fixed size L_{NH}, equal to \$138,600 in 2018 dollars (Table 3). It can occur again in a later year.

The bill reduces the money available for consumption, paid care, and saving. If the remaining resources are insufficient, the means-tested transfer described below provides the minimum consumption-and-care bundle. Retirees can save in advance to prepare for this possible expense.

[12] These estimates combine preferences with family exchange and other arrangements not separately modeled.

The model represents the financial cost of nursing-home use without a separate decision about where to live. Appendix B, B.5, explains how reported use becomes an annual bill probability.[13]

Government insurance. A means-tested transfer provides a minimum bundle of consumption and paid care (De Nardi, French, and Jones, 2010, 2016). For each health state, the government calculates the least expensive bundle that reaches utility $u_{\min}$, setting family care to zero for this calculation. When a retiree's cash on hand is below the cost of the bundle, the government pays the difference. The retiree receives the prescribed bundle and saves zero. The rule also covers healthy retirees with low resources, whether or not they receive a nursing-home bill.

The floor parameter sets the minimum consumption guaranteed to a healthy retiree. For retirees needing care, the same utility guarantee determines a bundle of consumption and paid care. I estimate the floor from receipt data using this simplified transfer rule.[14]

Budget and recursive problem. Assets earn interest at rate r and income is taxed progressively. Outside the transfer region, the within-period constraint is $c+p_{FC}l_{FC}+a' = x$, with $a' \geq 0$. Writing z for the persistent medical shock and π^d for the probability of death, the retiree solves

$$V_t(x,h,z;F,PI) = \max_{c,\,l_{FC},\,a'} \Big\{ u(c,l_{FC};h,l_{IC}) + \beta(1-\pi^d_{t,h})\,\mathbb{E}_t V_{t+1}(x',h',z';F,PI) + \beta\pi^d_{t,h}\,\theta(F)\tfrac{(\max\{a'-m_D,0\}+\kappa)^{1-\sigma}}{1-\sigma} \Big\}, \tag{3}$$

where $x' = (1+r)a' + y_{t+1} - m_{t+1}$, income y is net of tax, and m includes the additional expense when the nursing-home shock occurs. The transfer rule supplies the floor bundle whenever resources are insufficient. I solve the problem by backward induction for each income tercile and family type.

4 Estimation

I first estimate health, income, medical-expense, and care schedules separately by race. I then fit the saving model to White single women. Fitting the same model to Black single

[13] Family-care hours depend on health and type, including in years with a nursing-home bill. The bill changes the resources available for consumption, paid care, and saving. Ordinary medical spending and family-care schedules stay fixed in the policy experiments.

[14] The rule combines public support without modeling SSI, Medicaid categories, state provisions, or enrollment separately. A different fitted floor does not represent different statutory eligibility by race.

women shows which parameters change when the model faces Black starting resources, risks, and care arrangements.

4.1 First stage

I estimate income, health, medical spending, and care separately by race from the HRS. These estimates supply annual health, mortality, and nursing-home probabilities, spending and care profiles, and the starting sample. Appendix B gives the regressions and converts two-year health transitions to annual probabilities.

Simulated women start with the assets, health, medical spending, income, age, and assigned care type observed for single women in the 1996 sample.[15] I calibrate the estate deduction m_D separately by race from medical spending near death and death expenses, as described in Fact 6.

4.2 Fitting the saving model

I estimate the eight parameters governing care, bequests, patience, and public support by simulated method of moments (SMM). I choose values that bring the simulated outcomes close to White women's wealth, paid care, and Medicaid receipt, together with the pooled estate shares described above.[16]

I give less weight to noisier targets.[17]

I solve the saving problem numerically.[18]

I set the curvature parameters to $\sigma = 2.94$ and $\nu = 4.56$, the paid-care price to 12 in model units, and the nursing-home bill to 90,000 in model units.[19] Multiplying monetary model quantities by 1.54 converts them to 2018 dollars, giving a nursing-home bill of $138,600.

The estate deduction is $12,730 for White and $10,793 for Black decedents. I hold it fixed

[15] They enter at their observed ages, which can be older than 70.

[16] The parameters are $(\alpha_{\text{bad}}, \alpha_{\text{imp}}, \theta_{\text{rest}}, \theta_{\text{int}}, \kappa, \beta, \omega, c_{\text{floor}})$. Targets are median wealth by income tercile and age for two cohorts (66 possible cells, 60 valid), paid-care hours by health and type (4), estate shares by type (2) and tercile (3), and Medicaid receipt by tercile and health (6). Of 81 possible moments, 74 receive positive weight. I exclude healthy bottom-tercile receipt, which the single transfer rule fits poorly.

[17] I divide each model-data difference by its person-block bootstrap standard error, using 500 replications. In each replication, I recalculate the wealth and Medicaid income terciles, while keeping family-type assignments, first-stage schedules, and bequest tercile cuts fixed. This weighting gives less weight to noisier targets. The weighted differences describe fit; they are not independent standard normal test statistics. I report sandwich standard errors conditional on the first-stage estimates and type assignments, whose uncertainty is not fully included. Appendix D gives the weighting and standard-error calculations.

[18] I solve the saving problem by the endogenous grid method with an upper-envelope correction (Iskhakov, Jørgensen, Rust, and Schjerning, 2017). Optimization uses Nelder–Mead from one starting point and simulations use fixed seeds. Appendix C describes the solver.

[19] The curvatures come from the earlier two-state estimation.

Table 3: Second-stage estimates (White single women)

Parameter	Description	Estimate	(s.e.)	2018 $
β	Discount factor	0.972	(0.045)	–
α_{bad}	Care utility, bad health	0.025	(0.015)	–
α_{imp}	Care utility, impaired	173.3	(85.3)	–
θ_{rest}	Bequest intensity, none/moderate	66.2	(98.7)	–
θ_{int}	Bequest intensity, intensive	7.4	(17.7)	–
κ	Bequest luxury threshold	4,109	(2,336)	\$6,328
ω	Informal-care substitution weight	0.198	(0.110)	–
c_{floor}	Floor consumption equivalent	1,743	(405)	\$2,684
m_D	End-of-life deduction (calibrated)	8,266	–	\$12,730
σ, ν	Curvatures (fixed)	2.94, 4.56	–	–
L_{NH}	Nursing-home cost (calibrated)	90,000	–	\$138,600

Notes: Sandwich standard errors use the bootstrap covariance of the moment blocks, conditional on first-stage inputs and EM assignments. Model monetary units are multiplied by $\text{scale}_{2018} = 1.54$. Thus c_{floor} is \$2,684 a year and κ is \$6,328 of assets. The bequest coefficients are imprecise and can offset the bequest threshold: $\text{corr}(\hat{\theta}_{\text{rest}}, \hat{\kappa}) = 0.97$. Care weights and the floor can also offset one another: $\text{corr}(\hat{\alpha}_{\text{bad}}, \hat{c}_{\text{floor}}) = -0.32$ for White and -0.97 for Black estimates. The estimated ordering of the bequest coefficients is not a joint test of their equality.

and use the estate shares to estimate the bequest weights. None and moderate types share a weight because their observed estate shares are similar, 61.0 versus 60.4 percent ($t \approx 0.2$).[20]

Each set of targets describes a different part of the same saving decision. Wealth profiles show how many resources retirees keep at successive ages. Paid-care use shows how they divide spending when care is needed. Estates describe what remains for heirs, and Medicaid receipt shows when private resources are insufficient under the transfer rule. Fitting these outcomes together is useful because similar wealth paths can arise from different combinations of care needs, bequest motives, and public support. The policy comparisons depend on those combinations as well as on wealth itself.

Appendix F compares the baseline with alternative specifications for public-care aversion, family types, and the care aggregate.

Table 3 reports the estimates. The model places more weight on care in impaired than in bad health, consistent with paid-care use of 1.1 versus 0.15 hours per day. Appendix D explains how to interpret the care coefficients.

The estimate $\omega \approx 0.2$ means that an hour of family care contributes about as much to

[20]The weights can also absorb the effects of lifetime transfers and exchanges of care for bequests, which are outside the model.

utility as twelve minutes of paid care. A two-standard-error band ranges from zero to about twenty-five minutes.[21]

The model combines family and paid care linearly. Appendix F, F.4, compares this with the nonlinear alternative in Bueren (2023). I retain the simpler form, which fits about as well.

5 Results

I first check the fit and decompose the simulated racial wealth gap among older single women. I then examine wealth and estates across family types and the fit to Black data. Section 6 values a lower chance of a nursing-home expense and evaluates a subsidy that pays half the bill.

5.1 Model fit

The model fits 75 percent of the 60 valid wealth targets within one reported standard error and 90 percent within two.[22]

Figure 4 compares the model's wealth paths with the data. The bottom and top terciles track the data reasonably closely. In the middle tercile, the model predicts somewhat more wealth at ages 74–79 and a faster decline after age 80, where the data are noisy.[23]

The largest systematic differences concern Medicaid receipt among retirees needing care. In the middle tercile, the model predicts receipt in 21 percent of person-years, compared with 13 percent in the data. In the top tercile, it predicts 14 percent, compared with 5 percent. The simplified transfer rule therefore covers too many White women in these groups.[24]

The model underpredicts Medicaid receipt among healthy retirees in the bottom income tercile. I exclude this cell from the fitting objective.

Together, wealth, estate shares, and Medicaid receipt describe the private resources at risk and the support available when a bill arrives. The fit of these outcomes therefore matters for both the wealth decomposition and the policy valuations.

[21] This is a weight in the care-utility aggregate, rather than an estimate of how paid hours respond to an extra hour of family help.

[22] I calculate these shares only for cells with valid data targets. Wealth standard errors are bounded below by the larger of $2,000 and five percent of the cell's wealth level. The fit shares should therefore be read alongside the dollar differences in the figure.

[23] For the shares leaving an estate, the model-data differences are $t = 2.0$ and 0.2 by type and $|t| \leq 2.1$ by tercile. Paid-care differences reach 3.9 standard errors.

[24] The model-data differences are $t = 6.6$ and $t = 11.9$, respectively. Differences in eligibility, enrollment, family resources, or care not captured by the model may contribute to these gaps.

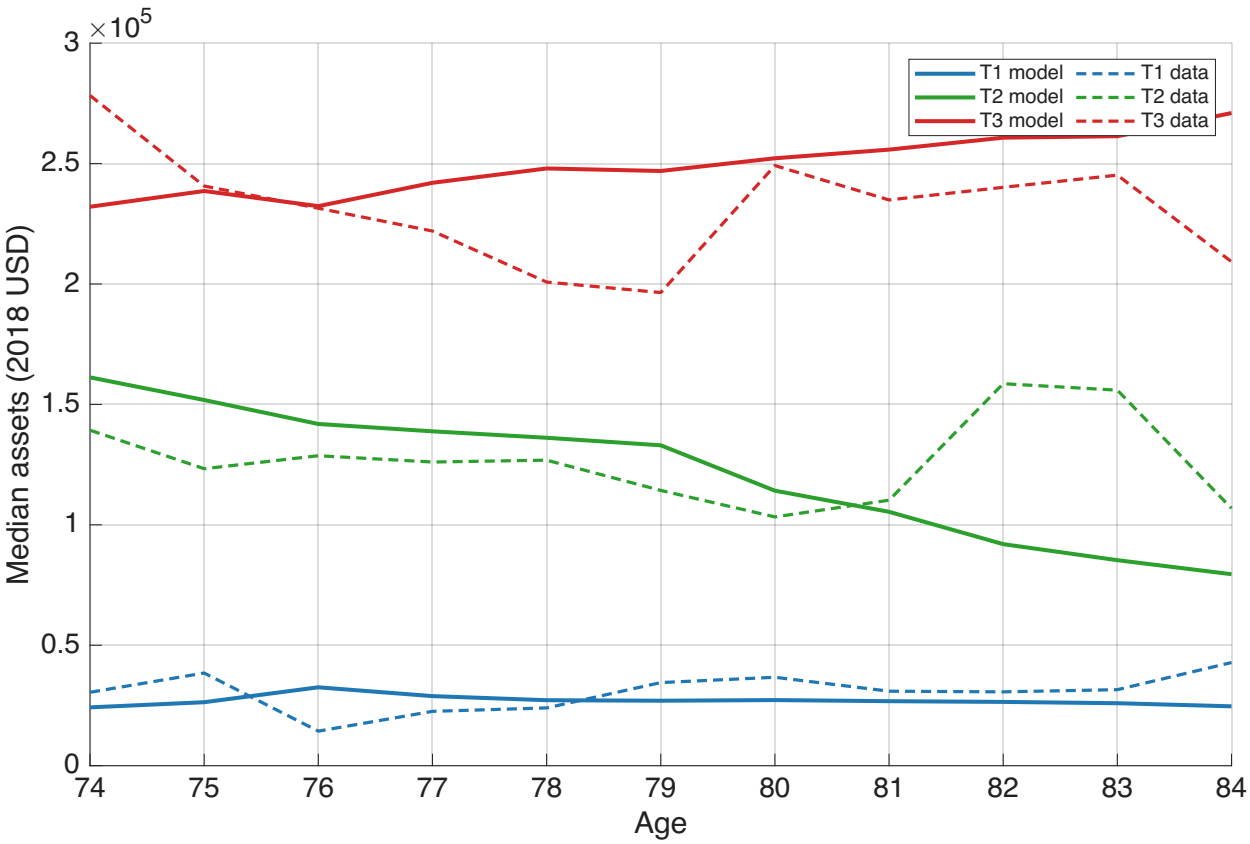


Figure 4: Model fit, White single women, cohort 1: median assets by age and income tercile, family types pooled at observed shares. Model (solid) vs. HRS (dashed), 2018 dollars.

5.2 Wealth persistence and initial conditions

I start with White women in the first cohort of the 1996 sample. I simulate their wealth using White inputs and again after switching the inputs to their Black counterparts. In each income third, I calculate median wealth at each age from 74 to 84 and average those medians. The difference between the two averages is the gap I seek to explain.[25]

Table 4 reports the contributions of starting resources, care groups, initial health, nursing-home probabilities, public support, and the remaining risk, income, medical-expense, and care schedules.[26]

Starting wealth and income account for 65 to 90 percent of the gap measured in dollars. Differences in the mix of family-care groups account for 11 to 19 percent. In logs, the care-group contribution is negative in the bottom tercile, where simulated Black median wealth is close to zero. Initial health contributes about 9 percent in the bottom and top income

[25] The floor component changes that fitted parameter; all other preference parameters remain at their White estimates. The contributions describe differences within the model, conditional on resources at sample entry.

[26] I average each component's contribution across all orders in which the inputs can change. These Shapley shares add up to the simulated gap. Appendix H.1 reports an alternative grouping of inputs.

Table 4: Decomposition separating starting wealth, health, and family type (single women, cohort 1, ages 74–84)

	Level of median wealth			Log of median wealth		
Component	T1	T2	T3	T1	T2	T3
Initial wealth and income position	65.4	89.7	70.3	64.2	93.4	76.4
Initial family type	19.0	12.0	10.8	−9.0	7.8	7.4
Initial health	8.8	−4.8	9.4	5.5	−2.3	7.1
Other processes (Table H.1)	5.5	2.7	7.7	14.3	1.5	7.9
Means-tested floor	4.4	2.4	2.2	26.4	1.7	2.2
Nursing-home probability	−3.2	−2.1	−0.4	−1.5	−2.2	−1.0
Gap	27,740	102,100	212,500	6.07	1.79	1.49

Notes: Shapley shares over all 2^6 combinations of inputs, for average median wealth over ages 74–84 and its log. Each starting sample uses the White 1996 file. Replacing wealth assigns the Black wealth value at the corresponding rank within tercile and cohort. Reweighting matches Black health and family-type shares. The wealth component also changes the tercile's income position. The floor takes the Black estimate while other parameters stay White. The remaining component groups risk, income, medical-expense, and care schedules. These components and starting samples differ from Table H.1, so the shares are not an exact split of that table. The all-Black bottom-tercile median is $64, making the log comparison sensitive to wealth close to zero.

thirds and reduces the gap in the middle. Differences in nursing-home probabilities narrow the gap; the floor accounts for 2 to 4 percent.

The middle income third illustrates the result: starting wealth and income account for 89.7 percent of the simulated gap, and the family-type mix accounts for 12.0 percent. The positive shares can exceed the total because other components offset them.

I give more or less weight to each care group until its share matches the share among Black women. The groups differ in their care hours, chances of a nursing-home bill, starting resources, and the weight the model puts on bequests. Appendix H.1 reports the separate within-type hours comparison.

The model begins with women already observed in old age. Earnings, marriage, inheritance, and other earlier experiences enter through their resources and circumstances at sample entry.

I next examine wealth and estates across these care groups and the fit to Black data.

5.3 Family types: wealth and estates in the model

I use estate shares pooled across single women and men as targets. Among retirees receiving intensive family care, 57.6 percent leave an estate in the model and 56.8 percent in the data.

For the other groups, the shares are 63.2 and 60.9 percent. A lower bequest weight for the intensive group helps the model match this pattern.[27]

I fit the model to median wealth by age and income, pooling the care groups. The ranking across care groups is a separate check. In the top income third, average median wealth over ages 74 to 84 is higher for women with moderate help ($285,000) than for those with little help ($246,000). Women with intensive help hold the least ($185,000). Fact 4 shows the same ordering in the data.

More family help reduces the paid care needed for a given level of care. A lower bill probability and a lower fitted bequest weight reduce reasons to retain assets. Starting resources also differ across groups. These features together can account for lower wealth among intensive-care retirees.

Section 6 values the lower probability of a nursing-home expense associated with intensive family care.

5.4 Fit to Black data

For the welfare comparisons, I also fit the model to Black single women using their own starting resources, care arrangements, and risks. The discount factor and the weight on family care remain close to the White estimates.[28]

The estimated consumption floor, which sets the minimum guaranteed to a healthy retiree, rises from $2,684 to $4,363 a year. Holding it at the White value and estimating the other parameters substantially worsens the fit. The higher floor helps the simplified rule match Black Medicaid receipt.[29]

The wealth decomposition uses common preference parameters apart from the floor component. For welfare comparisons, I allow the parameters to differ so that each race's valuations reflect its own fitted model.

Appendix H.4 reports the parameter estimates and detailed fit comparisons.

[27] The estimated ordering is $\theta_{\text{int}} < \theta_{\text{rest}}$. These weights summarize estate patterns and do not establish an exchange of care for bequests.

[28] With 457 Black women, precision is limited.

[29] The fitted floor summarizes public support under the model's rule; it does not represent different legal eligibility by race.

6 Protection against nursing-home expenses

Protection against a large nursing-home bill can be valuable to a retiree even when the mix of care groups explains a modest share of the wealth gap. I first lower the chance of a bill, then evaluate a subsidy covering half the expense. Full coverage provides a benchmark.

To value a change, I calculate the hypothetical one-time payment that would make a retiree as well off under the original arrangement as under the change. I make this calculation at her starting age and average across simulated retirees. She can adjust consumption, paid care, and saving over her remaining life, and the value includes her bequest motive. I call this wealth-equivalent variation.[30]

The value covers a change that lasts over the retiree's remaining life. It combines lower expected spending with protection against uncertainty, expressed as wealth she could use for consumption, care, or an estate.

6.1 The value of a lower chance of a nursing-home bill

In the data, retirees receiving intensive family care are less likely to report nursing-home use. The model assigns them a lower chance of a nursing-home bill. For an impaired White retiree at age 85, the annual probability is 0.18 for the intensive type and 0.43 for the none type.

In Table 5, I give retirees receiving little or moderate family care the intensive group's lower probability of a bill, within race, age, and health. The intensive group already faces this probability, so its gain is zero.

Among White women with little family care, the lower probability is worth an average of $78,000 in the bottom tercile and $236,000 in the top. The corresponding Black values are $12,000 and $95,000. The bottom-tercile value is roughly six times larger for White women, with a smaller ratio higher in the income distribution. Black moderate-care types gain almost nothing below the top tercile.

In the middle income third, the lower probability is worth an average of $131,000 for White women receiving little family care and $30,000 for Black women in that group.

Among women with little family care, the value rises with income for both Black and White women, consistent with greater private exposure to the bill among retirees with more resources. For a retiree with few assets, the model's public guarantee can cover more of the bill. Differences in the risk reduction and fitted preferences also enter these valuations.

[30] The hypothetical payment measures the retiree's gain and is separate from actual program payments. Each race uses its own estimates and income groups. The calculations exclude caregivers' welfare and the cost of financing.

Table 5: Value of giving each family type the intensive type's lower chance of a nursing-home bill, single women (thousands of 2018 dollars)

Family type	Race	T1	T2	T3
None	White	78	131	236
	Black	12	30	95
Moderate	White	81	131	199
	Black	2	0	15
Intensive	both	0	0	0

Notes: Average one-time payment under the original arrangement that would make a retiree as well off as with the intensive type's chance of a nursing-home bill. The calculation uses each type's 1996 initial draw. Only the probability changes. The bill, family-care hours, bequest preferences, and other parameters remain at their original values. Each race uses its own estimated parameters. The intensive type has no change and therefore no gain.

Table 6: Gains from nursing-home expense subsidies and gross program payments, single women

		Recipient value ($000)			Gross payments ($000)		
Instrument	Race	T1	T2	T3	T1	T2	T3
Subsidy, half	White	52	92	165	65	66	68
	Black	4	13	35	56	59	62
Subsidy, full	White	248	362	488	129	131	135
	Black	28	72	178	113	119	125

Notes: The subsidy pays half or all of each modeled nursing-home expense regardless of wealth. Retirees pay the uncovered share, with means-tested support available under the existing rule. Family-care hours and bill probabilities stay fixed. Recipient value is the average hypothetical one-time payment over retirees observed in 1996, valued at their entry ages, in thousands of 2018 dollars. Program costs are present values from a cohort-1 simulation, discounted from age 70 at $r = 0.02$. These are gross payments, before deducting changes in existing public transfers. Administrative costs and financing are excluded.

6.2 A subsidy covering half of nursing-home expenses

I consider a subsidy that pays half of the modeled nursing-home expense whenever the bill occurs. It is available at every wealth level, so retirees do not have to spend down their savings to receive it. They pay the uncovered share, with existing means-tested support available if their remaining resources are insufficient.

In the middle third of each race's income distribution, covering half the bill is worth $92,000 to White women and $13,000 to Black women (Table 6). The present values of gross payments are much closer, at about $66,000 and $59,000, respectively. Gross payments are what the subsidy pays before accounting for changes in existing public support.

The subsidy is worth more at higher incomes in both groups. In the model, women who

would pay the bill themselves have more money to spend or save. For women who would rely on means-tested support, the subsidy can take the place of some of that support. The model predicts more Medicaid receipt than the data show for White women needing care in the middle and top income thirds (Section 5). That matters because the same rule determines how much of the bill means-tested support would already cover.

As a benchmark, I also have the government pay the full bill. Gains more than double in every income third for both groups.[31]

Black women are more likely to be in the intensive-care group, which faces fewer nursing-home bills in the model. The two averages also reflect differences in starting resources, expense risks, and estimated preferences.

I report the other public-support comparisons in Appendix H. These exchange the fitted floor parameters and make cash payments calculated from the family-care hours retirees already receive.

7 Conclusion

I study how family care and long-term-care expenses contribute to racial differences in wealth among older single women. The White and Black women in the HRS differ in starting resources, health, family care, and Medicaid receipt. I estimate a saving model using these data, account for the simulated wealth gap, and value protection against nursing-home expenses.

Starting wealth and income account for 65 to 90 percent of the simulated wealth gap in dollars over ages 74–84. Differences in the mix of family-care groups account for 11 to 19 percent. This contribution combines the groups' care hours, nursing-home risks, fitted bequest motives, and starting resources.

Retirees receiving intensive family care get more help, face fewer nursing-home bills, and hold less wealth. The model also assigns them a lower weight on financial bequests to match their estate patterns. Giving retirees with little family care this group's lower bill probability is worth $131,000 for White women and $30,000 for Black women in the middle income third.

A subsidy covering half of nursing-home expenses is worth $92,000 for White women and $13,000 for Black women in that tercile. In the model, women who would pay the bill themselves keep more of their money. For women who would rely on means-tested support, the subsidy can replace some of that support.

Most of the racial wealth gap in old age persists from differences present at sample entry.

[31] These values measure gains under each group's resources, care arrangements, and estimated preferences. They are not measures of need.

Family arrangements contribute alongside those resources, and the value of additional public insurance depends on the expenses retirees would otherwise bear. A small contribution to the wealth gap can therefore coexist with a substantial value of protection against care expenses.

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A Data and sample construction

Source and sample. I merge the RAND and raw Health and Retirement Study (HRS) files for 1996–2018 with the helper and disability supplements. The supplements record care hours and the identity of helpers. I keep single, non-partnered respondents observed at age 70 or older and follow them until death or their last observed wave. Single includes never-married, divorced, widowed, and separated respondents. I exclude couples and observations from years spent married. The saving model, wealth decompositions, and policy valuations concern single women. Health, mortality, medical-expense, and income regressions also use single men and control for gender; I evaluate these profiles for women when solving the model. Family-care classification and schedules, nursing-home probabilities, and estate inputs use the broader single-retiree samples described below. The sample contains 2,008 White, 457 Black, and 163 Hispanic women, contributing 14,056, 3,199, and 1,141 person-waves.

Health and care needs. I use activities of daily living (ADLs: bathing, dressing, eating, transferring, walking, toileting) and instrumental activities (IADLs: using the phone, managing money, taking medications, shopping, preparing meals). A respondent is *healthy* with no limitations, in *bad* health with any IADL limitation or one–two ADL limitations, and *impaired* with three or more ADL limitations or an equivalent severe-disability flag. The data code `hstatus` as 3 for healthy, 2 for bad, and 1 for impaired; the model reverses this order. Medical spending can be positive in any living health state.[32][33]

Wealth. I use wealth from the prepared HRS extracts: financial assets, real estate other than the primary residence, vehicles, and business equity, net of debt. The measure excludes primary-residence equity. I treat this measured wealth as resources available to retirees in the model. Monetary amounts are in 2018 dollars unless identified as model units.

Permanent income. Following De Nardi, French, and Jones (2010), permanent income PI is the percentile rank of the household fixed effect $\hat{\alpha}_i$ from

$$\ln y_{it} = \phi(t, g_i) + \alpha_i + \varepsilon_{it}, \tag{4}$$

where y_{it} includes Social Security benefits and defined-benefit pension income, and $\phi(t, g)$ allows income to vary with age and gender. I use valid income observations outside the

[32] The earlier self-reported fair/poor indicator, inherited from De Nardi, French, and Jones (2010), disagrees with the care-limitation measure for about 15 percent of person-waves.

[33] Bueren (2023) separates physical and cognitive limitations. The model here uses the ADL/IADL groups without that distinction. Cognitive differences may also affect care and institutionalization.

two early AHEAD waves, whose income questions are less comprehensive. I cut terciles *within race*. Each tercile's model profiles use its observed mean pooled-PI rank: White $(0.24, 0.57, 0.86)$ and Black $(0.09, 0.32, 0.72)$. These replace the generic ranks $1/6, 1/2, 5/6$ and retain the Black groups' lower positions in the pooled income distribution.

Care. Care is classified by the identity of the helper. *Informal care* is unpaid help from relatives or friends; *formal care* is paid help from professionals (home health aides, visiting nurses, personal-care attendants). Hours are the sum of daily hours across helpers of each type; person-waves in a care-need state with no reported care of a given type are treated as zeros.

Estates and end-of-life expenses. HRS exit interviews with a proxy report the estate passed to heirs after a respondent's death. They also report out-of-pocket medical costs since the last core interview and death expenses, including funeral, burial, and legal costs.

Medicaid receipt at common income. Income groups differ across races. The Black middle tercile has a mean pooled-income rank of 0.32, compared with 0.57 for White retirees (Appendix A). Using common pooled-income terciles lowers the Black-to-White receipt ratios among retirees without care limitations from 3.7, 12.4, and 16.8 to 2.6, 4.7, and 4.9. The care-need ratios fall from 1.9, 3.2, and 2.8 to 1.5, 1.4, and 2.0.

B First-stage estimation

All first-stage processes are estimated separately by race and enter the saving model for single women as fixed inputs. The regressions with gender controls use women and men; the family-care and nursing-home schedules pool single women and men within each race, health state, and care group.

B.1 Health and mortality. I estimate survival and health transitions separately because death records lack the care and ADL modules. I use the full person-wave panel to retain death timing. A binary logit gives the two-year death probability from centered age $ac = (age - 85)/10$, ac^2, current-health indicators, centered permanent income, and gender. Among survivors, a multinomial logit gives transitions between living health states using the same regressors. I carry health forward within each person's records so that a death inherits her last observed state. I combine these estimates into a two-year Markov matrix $P^{(2)}(t, PI)$ with death absorbing. The matrix square root, $P^{(1)} = \left(P^{(2)}\right)^{1/2}$, gives annual transitions; I adjust

Table B.1: Informal-care hours per day, by family type and health

	Bad health			Impaired		
	None	Moderate	Intensive	None	Moderate	Intensive
White	0.05	0.74	3.79	0.17	1.22	10.09
Black	0.04	0.80	4.41	0.20	1.89	8.86

Notes: Mean daily hours of family-provided care among care-need single women and men, HRS 1996–2018, by the EM family type of Appendix E.

it to ensure valid probabilities. Table 1 reports the resulting life expectancies. Averaging across health states, Black women live 2.6 fewer years than White women, or 1.6 fewer at median permanent income in good health, and spend more of their remaining lives needing care.

B.2 Medical expenses. I separate ordinary medical expenses from spending on nursing homes, home health, hospice, and special facilities. The model represents long-term care through the nursing-home bill and the paid-care choice. Ordinary expenses include hospital, physician, outpatient, dental, drug, and other spending. I fit log spending with household fixed effects, a cubic age profile interacted with bad and impaired health, gender, and permanent income. I fit the residual variance using the same terms and compare the predicted profiles with raw cell medians. For White single women at age 80 and median permanent income, the profiles imply roughly \$1,080, \$1,210, and \$1,840 in healthy, bad, and impaired states. I represent persistent spending risk with a Tauchen grid (N_z points) and transitory risk with a separate grid (N_ε points).

B.3 Income. I estimate income profiles separately by race by regressing log annuitized income on a cubic in age, gender, permanent income, and its square. The coefficients enter the model's income profiles. As a check, I reconstruct the profiles and compare them with the existing inputs: White slope coefficients agree to three digits, and the age profiles have a correlation of 0.89. I apply the same procedure to the Hispanic sample in Appendix G.

B.4 Informal care by family type. I calculate mean daily family-care hours by race, care group, and health among observations with care needs (Table B.1). Intensive-care retirees receive roughly ten hours a day in impaired health, compared with a fifth of an hour for those receiving little care. The pattern is similar across races. Hours and nursing-home probabilities enter the model as separately estimated schedules.

B.5 Probability of a nursing-home bill. I record nursing-home use when a retiree reports any positive number of nursing-home nights in a care-need wave. Within each race, family type, and health state, I estimate its probability from age and age^2 using a logit. Cells with fewer than forty observations use the race-by-health logit. I convert the two-year probability p_2 into an annual probability as $1 - \sqrt{1 - p_2}$. For an impaired White retiree at 85, the annual probability is about 0.43 for the none type and 0.18 for the intensive type.

In each year with care needs, the model uses this probability to draw whether the retiree faces the nursing-home bill. Every bill has the same size. This maps observed use into an expense probability, with residence and stay duration outside the model. The probabilities describe differences across care groups and are taken as given.

B.6 End-of-life expense calibration. I use exit interviews for single female and male decedents aged 70 and older with an exit window of three to twenty-four months. I annualize reported medical spending since the last core interview by multiplying it by 12/months alive, then deflate it to 2018 dollars. I deflate death expenses separately. The medical measure describes annualized spending over the exit window.

Median medical spending is \$2,267 for White and \$527 for Black decedents. Median death expenses are \$10,463 and \$10,265. Adding these separate medians gives estate deductions of \$12,730 and \$10,793. I hold each race's deduction fixed across experiments. The two components can use different observations, so their sum need not equal the median of total expenses. Out-of-pocket spending also reflects both financing and care use.

B.7 Initial distribution. I draw each simulated woman's starting assets, health, medical shock, income, age, and family type from their joint distribution among single women in the 1996 sample, separately by race, tercile, and cohort. Cohorts are defined by age in 1996 and followed over different age ranges. Wealth targets cover ages 74–84 for the first cohort and 84–94 for the second.

C The dynamic problem and its numerical solution

C.1 Recursive problem. A retiree of family type F and permanent income PI chooses consumption c, purchased formal care l_{FC}, and next-period assets $a' \geq 0$ to solve

$$V_t(x,h,z;F,PI) = \max_{c,l_{FC},a'\geq 0} \Big\{ \frac{c^{1-\sigma}}{1-\sigma} + \alpha(h)\frac{[l_{FC}+\omega l_{IC}(h,F)]^{1-\nu}}{1-\nu} + \beta(1-\pi^d_{t,h})\,\mathbb{E}_t\,V_{t+1}(x',h',z';F,PI) + \beta\pi^d_{t,h}\,\theta(F)\frac{(\max\{a'-m_D,0\}+\kappa)^{1-\sigma}}{1-\sigma}\Big\}, \tag{5}$$

outside the transfer region, subject to $c + p_{FC}l_{FC} + a' = x$ and next-period cash-on-hand $x' = (1+r)a' + y_{t+1}(PI) - m_{t+1}$, where y is net of tax and m_{t+1} includes the out-of-pocket medical draw and, with probability $\pi_{NH}(t{+}1,h',F)$ in a care-need state, the nursing-home expense L_{NH}. The medical shock z follows the discretized AR(1) of Appendix B. The government floor sets $c = c(h)$, $l_{FC} = l_{FC}(h)$, $a' = 0$ whenever x falls below the state-specific threshold $\underline{x}(h)$ at which the floor bundle is affordable.

C.2 Formal-care choice. At an interior optimum, the marginal utility of paid care equals its price times the marginal utility of consumption: $\alpha(h)[l_{FC} + \omega l_{IC}]^{-\nu} = p_{FC}\,c^{-\sigma}$. This condition gives paid-care hours as an increasing function of consumption. Substituting this choice into the dynamic problem leaves consumption and saving to be chosen in each (h,z) cell.

C.3 Solution method. The government floor makes the value function non-convex. I use the endogenous grid method with an upper-envelope correction (Iskhakov, Jørgensen, Rust, and Schjerning, 2017). At each grid point for next-period assets, I calculate Euler-equation consumption $c = \big(\beta\mathbb{E}[\ldots]\big)^{-1/\sigma}$, paid care, total expenditure, and current cash on hand. Near the floor, several consumption choices can correspond to the same cash level. I compare their values and keep the best choice at each point. Tracking value and its derivative produces both policy and value functions, including the functions used in Section 6. I use a square-root-spaced cash grid (N_x points), a Tauchen medical grid ($N_z \times N_\varepsilon$), and the three health states for every race, income tercile, and care group. Replacing the earlier golden-section solver with DC-EGM reduced the cost of a full moment evaluation by more than an order of magnitude and made the comparisons in Appendix F feasible.

D Simulated method of moments and inference

D.1 Estimator. The eight estimated parameters $\Theta = (\alpha_{\text{bad}}, \alpha_{\text{imp}}, \theta_{\text{rest}}, \theta_{\text{int}}, \kappa, \beta, \omega, c_{\text{floor}})$ minimize

$$Q(\Theta) = \left[m^s(\Theta) - m^d\right]' W \left[m^s(\Theta) - m^d\right], \qquad W = \text{diag}(1/\hat{s}_j^2), \tag{6}$$

where m^d contains the 81 White data targets, $m^s(\Theta)$ their simulated values, and $\hat{s}_j$ the bootstrap standard error of target j. The objective adds the squared differences after scaling each by its standard error. These are fit differences, not independent test statistics. Following Altonji and Segal (1996), I use diagonal weights. Simulations use fixed seeds and $N_{\text{sim}} =$ 2,000 retirees per cell. I optimize by Nelder–Mead from a single starting point.

D.2 Moments. The moment vector has 81 cells, of which 74 carry positive weight in the White objective and 71 in the Black one; a cell is dropped when either its data value or its bootstrap standard error is undefined (thin cohort-2 wealth cells at the oldest ages), and the bottom-tercile healthy Medicaid cell is zero-weighted by construction (Section 5). Counts quoted in the text refer to weighted moments. The 81 cells are: median wealth by tercile and age, pooled across family types, for two cohorts (ages 74–84 and 84–94; 66 cells); formal-care hours by severity × family type (4); bequest incidence by family type (2) and by tercile (3); and Medicaid receipt by tercile × health (6). Wealth is pooled across family types because type-specific wealth-by-age cells are thin and their bootstrap variances unreliable; care and estate targets help determine the type-specific parameters. The care-history mixture is estimated separately.

D.3 Bootstrap weights. I estimate standard errors $\hat{s}_j$ with a person-block bootstrap using $B = 500$ replications. Each replication resamples people and keeps their records together. I recalculate the wealth and Medicaid income cuts while retaining the bequest cuts, care-group assignments, and first-stage schedules. To prevent nearly degenerate cells from dominating, standard errors are bounded below by the larger of \$2,000 and five percent of the wealth level, 0.02 hours for care, 0.01 for incidence, and 0.005 for Medicaid receipt.

D.4 Parameter information and uncertainty. Paid-care hours across health states help estimate the care weights, and differences across care groups help estimate ω. Medicaid receipt helps estimate the floor. Wealth paths help estimate patience, β, and estate shares help estimate the bequest weights and threshold. All these outcomes jointly determine the estimates because the parameters also affect future utility and saving.

The bequest coefficients and threshold are imprecise and closely related: $\text{corr}(\hat{\theta}_{\text{rest}}, \hat{\kappa}) =$

Table D.1: Second-stage estimates and standard errors for single women, by race

	White		Black	
Parameter	Estimate	(s.e.)	Estimate	(s.e.)
β	0.972	(0.045)	0.974	(0.065)
α_{bad}	0.025	(0.015)	0.005	(0.003)
α_{imp}	173.3	(85.3)	157.4	(116.0)
θ_{rest}	66.2	(98.7)	640.8	(997.9)
θ_{int}	7.4	(17.7)	5.7	(45.9)
κ	4,109	(2,336)	36,658	(22,358)
ω	0.198	(0.110)	0.207	(0.166)
c_{floor}	1,743	(405)	2,833	(641)

Notes: I fit each race to its own data, using its observed starting characteristics and estimated schedules. Sandwich standard errors condition on first-stage inputs and family-type assignments. The bequest pair is imprecise. The estimated Black correlation between the care weight and floor is -0.97. Fixing the floor at the White estimate worsens fit; this comparison does not test eligibility rules.

0.97 for White and 0.91 for Black estimates. Lockwood (2018) discusses the difficulty of distinguishing bequest parameters. The estimated ordering alone is not a joint test of equal coefficients. Care weights and the floor can also offset one another; their reported Black correlation is -0.97. Fixing the floor at the White estimate compares fit within this specification, rather than testing whether eligibility rules differ.

Table 3 reports the estimates. The weight on care is much higher in impaired than in bad health ($\alpha_{\text{imp}} \gg \alpha_{\text{bad}}$), consistent with greater paid-care use: 1.1 versus 0.15 hours per day. The weight enters the care demand equation through $\alpha^{1/\nu}$ when consumption and family care are held fixed. With $\nu = 4.56$, a care weight roughly seven thousand times larger produces about seven times as much of this component of care demand.

D.5 Standard errors. Because $W \neq \hat{S}^{-1}$, the estimator is not efficient and standard errors use the sandwich

$$\widehat{\text{Var}}(\hat{\Theta}) = (G'WG)^{-1}G'W\,\hat{S}\,WG\,(G'WG)^{-1}, \tag{7}$$

where $G = \partial m^s/\partial\Theta'$ is the numerical moment Jacobian at the optimum (central differences in natural units) and $\hat{S}$ is the full bootstrap covariance of the data moments, taken block-diagonal across the independent bootstrap frames. Table 3 reports the White estimates and Table D.1 reports both races. The standard errors are conditional on the first-stage inputs and family-type assignments.

E Family-type classification: the care-history mixture

E.1 Specification. Family type is recovered from complete informal-care histories by a K-component zero-inflated lognormal mixture. A person contributes her sequence of care-need waves; type k generates, in each such wave, no care with probability $1 - p_k$ and otherwise daily hours drawn lognormal(μ_k, s_k^2). Person i's likelihood multiplies the per-wave densities, and the population likelihood is

$$\mathcal{L} = \prod_i \sum_{k=1}^{K} \pi_k \prod_{w \in W_i} \Big[(1 - p_k)\mathbf{1}\{c_{iw} = 0\} + p_k \, f_{\text{LN}}(c_{iw}; \mu_k, s_k)\mathbf{1}\{c_{iw} > 0\} \Big], \tag{8}$$

I estimate the mixture by expectation-maximization (EM). The expectation step calculates each person's probabilities of belonging to the care groups. The maximization step updates (π_k, p_k, μ_k, s_k). For people never observed needing care, I draw a type from the prior π using a fixed seed. Their histories supply no care-need observations for classification.

E.2 Number of types. The Bayesian information criterion (BIC) favors $K = 3$ over $K = 2$: 18,747 versus 18,921 (Table E.1). The probabilities of any care are 0.12 for the none group, 0.49 for moderate, and 0.53 for intensive. When care is positive, median daily hours are 0.6, 0.8, and 5.8, respectively. Among classified observations, the intensive group's share is 0.19 for Black and 0.09 for White retirees. The shares at model entry differ because they use a different sample. None and moderate groups have similar estate shares, 61.0 versus 60.4 percent ($t \approx 0.2$), so they share a bequest weight. I treat care type as fixed during retirement.

The assigned care groups have different shares in different samples. At model entry, intensive-care retirees account for 23 percent of Black and 11 percent of White women. Across all observed person-waves, the shares are 19 and 9 percent. Table E.1 reports the mixture prior and shares after assignment; the model starts with assigned types. Among decedents with observed care histories, the shares leaving an estate above \$1,000 are 46 percent for intensive-care retirees and 58 percent for the other groups.

E.3 Classification uncertainty. I check sensitivity to classification by drawing each retiree's type from her posterior distribution, rebuilding the type-specific inputs and moments, and estimating the model again. The resulting objective is $Q = 282$. Because the draw changes the target moments, this value is not directly comparable with the baseline objective.

With the new type draw, estimates are $\beta = 0.972$, $\omega = 0.18$, and $c_{\text{floor}} = 1{,}473$ in model

Table E.1: Care-history mixture: $K = 2$ versus $K = 3$

	$K = 3$ (BIC-preferred)		
	None	Moderate	Intensive
Mixture prior π_k (estimated)	0.53	0.30	0.17
P(any care | care-need wave)	0.12	0.49	0.53
Median hours/day (when positive)	0.6	0.8	5.8
Share, White single women (modal assignment)	0.67	0.24	0.09
Share, Black single women (modal assignment)	0.62	0.19	0.19
	Fit		
Log-likelihood, $K = 2$ / $K = 3$	−9,433 / −9,330		
BIC, $K = 2$ / $K = 3$	18,921 / 18,747		

Notes: Zero-inflated lognormal mixture on HRS care histories, single women and men 70+, both races pooled. BIC prefers $K = 3$.

units, compared with reference values of 0.972, 0.20, and 1,743. The intensive group retains its lower bequest weight. The bequest and care-floor pairs move within combinations that have substantial estimation uncertainty. The exercise checks sensitivity to type assignment while continuing to treat care arrangements as given.

F Specification choices and robustness

This appendix compares the baseline with alternative specifications for public-care aversion, end-of-life expenses, family types, and the care aggregate.

F.1 Public-care aversion. I allow a utility penalty through $c_G < c_{\text{floor}}$ in care states (Ameriks, Briggs, Caplin, Shapiro, and Tonetti, 2020). Using the same numerical settings, the objectives are 278 without aversion and 284 with it. Medicaid receipt changes little. I retain the simpler specification.

F.2 End-of-life expenses: a calibrated deduction. I set m_D to the sum of median annualized medical spending near death and median death expenses (Appendix B, B.6). This keeps the deduction separate from the bequest parameters, which also fit estate shares. The sum of separate medians summarizes expenses; it need not equal the median of total liabilities. I hold it fixed within race and across experiments.

F.3 Two versus three family types. The two-type specification combines the none and moderate groups. It uses the same targets and number of estimated parameters as the three-

type model. The estimates of β, ω, and the floor are similar, and the intensive group retains its lower bequest weight. I use three types because BIC favors them and they preserve the observed care differences. This comparison concerns parameter estimates; it does not recalculate every policy value under each classification.

F.4 The care aggregate: linear versus CES. The baseline combines care as $l_{FC} + \omega l_{IC}$. I compare it with the CES form in Bueren (2023), $[\tau l_{FC}^{\varpi} + (1-\tau) l_{IC}^{\varpi}]^{1/\varpi}$. With $(\tau, \varpi) = (0.55, 0.06)$ fixed, re-estimating the care levels gives objective 313, compared with 294 for the linear specification under the same numerical settings. Estimating the CES parameters with the full vector gives 293.6 versus 294.1. The CES parameters remain at their starting values, $(0.550, 0.059)$. The two fitted objectives are approximately equal at these settings.

At $\varpi = 1$, the CES formula can reproduce the linear form. The factor $\tau^{1-\nu}$ rescales the care coefficients, and $(1-\tau)/\tau$ takes the role of ω. Given the similar fit, I use the simpler linear aggregate for the experiments.

G A pooled model with common parameters

Here I estimate a common parameter vector for White and Black single women, using their targets together with the pooled estate inputs described above. Each group keeps its health, mortality, medical spending, income, nursing-home probabilities, family care, starting resources, and estate deduction m_D. I pool the wealth, estate, and Medicaid targets and retain separate paid-care targets. The racial wealth gap is not directly targeted, so I also inspect each race's wealth predictions.

G.1 Two races. The common-parameter model uses 78 weighted targets and has objective $Q = 254.5$. Among White wealth predictions, 82 percent fall within one reported standard error and 95 percent within two; the Black shares are 74 and 93 percent. These separate paths are not estimation targets. Estimates include $\beta = 0.971$, $\omega = 0.24$, $\theta_{\text{int}} = 5.3$, and $c_{\text{floor}} = 2{,}552$ in model units. Monetary parameters in this appendix are in model units; Table 3 converts them to 2018 dollars.

For the pooled estate shares, $|t| \leq 1.6$. Medicaid receipt differs by $t = 9.6$ in the top and 3.3 in the middle income tercile. A common parameter vector captures much of the separate wealth pattern, while receipt gaps remain under the simplified transfer rule.

G.2 Adding Hispanic single women. An exploratory three-group extension uses the same construction for Hispanic single women. The intensive-care share among initial single

women is 27 percent, compared with 23 for Black and 11 for White women. The Hispanic exit sample is too small to calibrate m_D reliably, so the exercise uses the Black deduction as an explicit approximation.

With all three groups, the fit uses 89 weighted targets and has objective $Q = 219$. The shares of separate wealth predictions within one and two reported standard errors are 77 and 97 percent for White, 74 and 95 for Black, and 75 and 86 for Hispanic retirees. These paths are not separately targeted. The Hispanic starting sample has 149 observations, limiting precision. The floor is 3,467 in model units. Its change with the target population shows how the simplified guarantee responds to the receipt patterns being fitted.

H Additional decompositions and policy comparisons

H.1 An alternative decomposition and changes in wealth

Starting sample for the main decomposition. I construct each starting sample from observations of White single women. To change wealth, I assign each retiree the Black wealth value at the corresponding rank within her income tercile and cohort. To change health or family type, I reweight observations to match the Black shares in each group. This keeps some relationships among the White starting characteristics. The alternative decomposition below uses different starting samples, so its initial-condition share is not an exact sum of the main decomposition's components.

The main text separates starting wealth, health, and family type. This alternative calculation replaces the entire initial distribution together and separates the later income, health, medical-expense, and family-care inputs. It uses each race's observed starting sample rather than constructing both samples from White observations. Preferences remain at the White estimates.

Table H.1 changes five groups of inputs. For each group, I average its effect across all orders in which the inputs can be replaced. These Shapley contributions add up to the total simulated gap. The one-at-a-time column instead replaces each input starting from the White baseline. Those effects overlap and need not add up to 100 percent. The difference between the columns shows how an input's contribution depends on which other inputs have already changed.

The resources and circumstances present at sample entry account for 86 to 95 percent of the wealth-level gap. Among the later income, health, medical-expense, and care inputs, the largest contribution is the Black income profile in the bottom tercile, about 10 percent. The other contributions are smaller after allocating their interactions. This result concerns the

Table H.1: Decomposition of the racial wealth-path gap (single women, cohort 1, ages 74–84)

	Shapley (order-invariant)			One-at-a-time		
	T1	T2	T3	T1	T2	T3
Health, mortality, and NH risk	3.5	4.6	2.5	11.4	13.9	1.6
Medical expense process	−1.3	−0.1	2.9	10.4	3.1	−0.9
Income profile	10.1	−1.5	2.2	5.7	2.6	7.7
Informal care hours	1.3	1.8	0.4	8.1	9.7	−0.9
Initial distribution (incl. family type)	86.4	95.1	92.0	90.9	99.3	95.1
Sum	100	100	100	126.5	128.5	102.7
Gap (2018 $, simulated)	28,800	105,178	211,877	28,800	105,178	211,877

Notes: Reported shares of the simulated all-White to all-Black gap in the mean of age-specific median assets over ages 74–84, using 32 scenarios. Shapley shares average each component's contribution across all switch orders and sum to 100. The one-at-a-time column switches each component from the White base; overlap means those shares need not sum to 100. A negative entry means the switched component raises the simulated wealth path.

persistence of a large initial wealth gap; it does not measure the value of health or insurance to retirees.

Table 4 also reports the decomposition in logs. The ranking is similar above the bottom tercile. In the middle and top terciles, wealth accounts for 93 and 76 percent, care group for 8 and 7, health for −2 and 7, other processes for 2 and 8, and the floor for 2 and 2. In the bottom tercile, the floor accounts for 26 percent. The simulated all-Black median there is only $64, while the data median is $0 at ages 75–78. Logs are sensitive to these near-zero values.

I also decompose the racial difference in the change in median wealth between ages 74 and 84. In the bottom tercile, this difference is only $2,000, so component shares can exceed ±100 percent. Starting resources account for most of the middle-tercile difference; the top tercile has a different ranking. The change calculations give no common explanation across the income groups.

H.2 Sensitivity to the fitted consumption floor

In Table H.2, I give White retirees the floor estimated from Black data and Black retirees the floor estimated from White data. All other inputs retain each group's own values. This checks the role of the minimum guarantee in the model's welfare, saving, and receipt predictions. It is a parameter comparison, rather than a change in legal eligibility.

White retirees gain an average of $41,000 to $62,000 from the higher floor, while Black retirees lose $59,000 to $75,000 from the lower one. White median wealth declines by one and

Table H.2: Sensitivity to exchanging the fitted consumption-floor parameters, single women

	T1	T2	T3
Wealth-equivalent value (thousands of 2018 dollars)			
White retirees given the Black floor	+41	+48	+62
Black retirees given the White floor	−75	−59	−69
Median wealth path, ages 74–84			
White, change at the Black floor	−1.5%	−2.8%	−2.3%
Medicaid receipt in care-need states			
Black, own floor → White floor	0.70 → 0.37	0.33 → 0.21	0.15 → 0.14
White, own floor (for reference)	0.31	0.20	0.14

Notes: The floors fitted to White and Black data are $2,684 and $4,363 a year in 2018 dollars (Table H.4). Only c_{floor} changes; all other parameters, starting characteristics, and schedules remain at each group's own values. Values are average one-time payments over the 1996 starting sample. Positive values denote gains and negative values losses. The group names describe the data used to estimate each floor, rather than different racial eligibility rules.

a half to three percent. The guarantee can therefore have substantial value while changing wealth levels little. It accounts for only 2 to 4 percent of the wealth gap in Table 4.

Among Black retirees needing care in the bottom tercile, receipt falls from 0.70 to 0.37 under the lower floor. White receipt at its baseline floor is 0.31. The guarantee thus helps account for the model's receipt gap. The comparison describes receipt under different model guarantees.

In the middle tercile, Black retirees with little family care lose $83,000 from the lower floor, compared with $31,000 for moderate and $33,000 for intensive types. The largest loss is among those with the least family help. These comparisons also reflect differences in starting resources and bequest coefficients across types.

Means testing helps explain the results. Public payments protect resources that retirees would otherwise spend themselves. When existing support already pays an expense, a new subsidy can replace that payment. The model combines eligibility provisions in a single rule, so this comparison concerns the value of the guarantee.

H.3 Cash payments for existing family-care hours

As an alternative to the nursing-home subsidy, I calculate a cash payment for a single woman based on the family-care hours she already receives.

For each hour of help received from relatives or friends, I calculate a payment of $8 in model units, about $12.30 in 2018 dollars. The full amount is charged to the program. I

Table H.3: Gains from cash payments for family-care hours and gross program payments, single women

		Recipient value ($000)			Gross payments ($000)		
Instrument	Race	T1	T2	T3	T1	T2	T3
Care transfer, full	White	36	40	44	26	24	22
	Black	56	90	64	50	60	53
Care transfer, half	White	22	21	22	26	24	22
	Black	35	65	38	50	60	53

Notes: Care transfers are cash payments calculated at $8 per family-care hour in model units (about $12.30 in 2018 dollars), using hours already received in care-need states. All or half of this payment reaches the retiree; the program pays the full rate in either case. Hours and bill probabilities stay fixed. The payment enters the retiree's cash on hand and can replace existing floor support. Recipient value is the average hypothetical one-time payment over retirees observed in 1996, valued at their entry ages. Program costs are present values from a cohort-1 simulation, discounted from age 70 at $r = 0.02$. These are gross payments, before deducting changes in existing public transfers. Caregiver welfare, changes in hours, administrative costs, and financing are excluded.

consider cases in which all or half reaches the retiree as cash she can spend. The family-care hours are those she already receives.

The cash payment for family care is worth more per Black retiree. In the middle tercile, its value when the full payment reaches the retiree is $40,000 for White and $90,000 for Black retirees. For none, moderate, and intensive types, the White and Black values are respectively $4,000 and $2,000, $37,000 and $50,000, and $231,000 and $284,000. Paying for existing hours directs more money to intensive-care families, which are more common among Black retirees. Differences remain within types as well.

Paying for more hours also costs more. In the middle tercile, annual gross payments average $6,100 per Black retiree and $2,600 per White retiree.

The calculation values the money reaching the retiree under her existing care arrangement. Family hours and nursing-home probabilities stay fixed. Caregivers' time costs and welfare are outside the measure, including any benefit from a share of the payment they retain.

H.4 Detailed fit to Black data

Using White parameters with Black starting characteristics, schedules, and estate deduction m_D, 14 of 71 weighted targets differ from the data by more than two reported standard errors. The largest misses are too many estates ($t = 6.2$ and 4.3 by type) and too little middle-tercile Medicaid receipt ($t = -5.2$). Wealth and care hours fit more closely.

Fitting the eight parameters to Black data lowers the objective from 410 to 107 and

Table H.4: Estimates for Black single women

	Parameter	White (s.e.)	Black
Near White	Discount factor β	0.972 (0.045)	0.974
	Care utility α_{imp}	173.3 (85.3)	157.4
	Informal-care weight ω	0.198 (0.110)	0.207
	Bequest, intensive θ_{int}	7.4 (17.7)	5.7
Unresolved	Care utility α_{bad}	0.025 (0.015)	0.005
Shifted	Floor c_{floor} (2018 \$)	\$2,684 (624)	\$4,363
	Bequest threshold $(\theta_{\text{rest}}, \kappa)$	(66, \$6.3k)	(641, \$56.5k)

Notes: Each race uses its own starting characteristics, schedules, and m_D. "Near White" means within one White standard error; for β, the range is 0.927 to 1.017. The bad-state care weight falls fivefold and lies outside this range, but its comparison gives $t = 1.3$. Its correlation with the Black floor is -0.97. The bequest pair is imprecise. Appendix D reports standard errors.

reduces the number of differences exceeding two reported standard errors from 14 to 6.[34] In Table H.4, the discount factor, family-care weight, impaired-state care weight, and intensive-group bequest weight are within one White standard error. With 457 Black women, precision is limited. The White one-standard-error reference range for β is 0.927 to 1.017.

The bad-state care weight α_{bad} falls fivefold, by more than one White standard error. A covariance-based comparison gives $t = 1.3$; the implied difference in paid-care hours is about forty percent. The care weight and floor can offset one another, with $\text{corr}(\hat{\alpha}_{\text{bad}}, \hat{c}_{\text{floor}}) = -0.97$.

The floor rises from \$2,684 to \$4,363 a year. Fixing it at the White value and estimating the other seven parameters raises the objective from 107 to 217.[35] Despite a threefold rise in the bad-state care weight and near tripling of the impaired-state weight, middle-tercile receipt stays low ($t = -3.1$). Allowing the floor to change improves fit.

The common-income comparisons in Fact 7 leave assets, eligibility, and geography uncontrolled. The model also underpredicts healthy bottom-tercile receipt: 0.005 versus 0.153 for White retirees, and 0.245 versus 0.568 for Black retirees. Its Black-to-White ratio is roughly fifty, compared with 3.7 in the data. Only the bottom-tercile healthy cell of Table 2 is excluded from estimation. The other rows help estimate the floor and therefore supply no separate test of it.

[34] Objectives are comparable only with the same targets and weights. Wider Black standard errors prevent comparison with the White objective. The pooled exercises in Appendix G also use different targets.

[35] Under diagonal weights, the difference is not χ^2 distributed.

The higher floor helps the single transfer rule match receipt. It can absorb differences in enrollment, eligibility provisions not modeled separately, and measurement.[36]

The bequest pair $(\theta_{\text{rest}}, \kappa)$ also changes as the model fits the Black estate share of 36 percent. Both estimates are imprecise, so their movement alone cannot establish a stronger bequest motive. Receipt gaps also remain in the common-parameter exercise of Appendix G.

[36]SSI-related and medically-needy eligibility operate within common rules. Fact 7 does not separately observe eligibility and take-up.