Online Appendix for: “Beyond Income: Health, Wealth, and Racial/Ethnic Welfare Gaps Among Older Americans”

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A Multiple imputation of consumption and other missing data

We follow the procedure of Miller and Bairoliya (2022) to impute consumption and other missing HRS data. This procedure uses the bootstrapping approach for cross-sectional time-series data proposed by Honaker and King (2010) and implemented through the Amelia II software program (Honaker et al., 2011). We use the program to produced twelve complete datasets without missing data and all analyses are conducted on each dataset then combined into a single estimate. We follow Miller and Bairoliya (2022) in selecting the following variables for the imputation model: number of household members, age, aged squared, cubed root of total wealth, log household income, and dummy indicators for cohort, labor force status, gender, race, education, marital status, census division, 1980 census occupation code for longest reported tenure, self-reported health, ADLs, and eight doctor diagnosed health conditions. Additionally, our model accounted for retirement, hours worked, and an alternate measure of consumption that included health spending. To account for the time-series nature of the data, we included lags and leads of consumption, wealth, income, and hours worked in our imputation model. Interested readers can consult the appendix in Miller and Bairoliya (2022) for further details and diagnostic tests that indicate the procedure's effectiveness in imputing missing data in the HRS dataset.

B Forecasting model

In this section we detail our estimation and simulation procedures, which also closely follow those used by Miller and Bairoliya (2022).

B.1 Higher order lags

In order to avoid autocorrelation within the structural error terms of the model, it may be necessary to consider additional outcome lags. An extension of the VAR(1) model to higher orders is straightforward, as seen with the following VAR(2) version of our model:

$$AY_{it} = BY_{it-1} + DY_{it-2} + CX_{it} + \varepsilon_{it},$$

with the block matrix form of DY_{it-2} given by:

$$\left[\begin{array}{c|cccc} D_{11} & D_{12} & D_{13} & D_{14} & D_{15} \\ \hline D_{21} & d_{22} & d_{23} & d_{24} & d_{25} \\ D_{31} & d_{32} & d_{33} & d_{34} & d_{35} \\ D_{41} & d_{42} & d_{43} & d_{44} & d_{45} \\ D_{51} & d_{52} & d_{53} & d_{54} & d_{55} \end{array}\right] \left[\begin{array}{c} M_{it-2} \\ \hline s_{it-2} \\ r_{it-2} \\ c_{it-2} \\ w_{it-2} \end{array}\right].$$

For example, the coefficient vector D_{51} in this model allows the second lag of the morbidity state vector to have a direct effect on current wealth. We can also shut down any specific lag by setting the appropriate coefficient to zero. For example, excluding the second lag of self-rated health on wealth simply implies setting $d_{52} = 0$.

B.2 Estimation

The forecasting model was estimated using a pooled sample of individuals born before 1960 who were aged fifty or older at the time of the survey. The sample included 40,708 unique individuals and a total of 238,091 individual-year observations. Table 1 presents descriptive statistics for each cohort in the HRS.

Table 1: Estimation sample descriptive statistics by cohort

	AHEAD	CODA	EHRS	LHRS	WB	BB	MBB	LBB
Individuals	7,651	4,137	5,255	5,138	3,529	4,610	5,131	4,200
Observations	36,679	27,946	45,283	46,623	28,290	24,761	18,761	5,506
Age (mean)	81.76	75.23	67.64	62.74	60.46	58.46	55.34	52.68
Hypertension (%)	54.76	57.39	53.57	50.73	49.62	49.75	47.65	45.34
Diabetes (%)	15.48	18.85	19.45	18.16	18.33	20.18	19.54	19.62
Cancer (%)	16.94	18.02	14.20	11.19	10.67	8.64	7.72	6.93
Lung disease (%)	9.48	10.19	9.57	8.52	7.20	7.01	7.67	7.59
Heart disease (%)	35.41	31.11	23.18	19.25	16.72	14.79	12.56	10.45
Stroke (%)	15.34	12.26	7.49	6.03	5.73	5.02	4.42	4.32
Psyche problem (%)	11.89	11.59	11.17	12.93	16.94	19.26	19.62	20.08
Arthritis (%)	56.06	60.25	57.59	52.70	51.81	46.35	40.01	33.01
Difficulty with ADLs (%)	40.44	28.87	23.95	21.72	21.97	21.36	19.71	14.94
Self-rated health (%)								
Poor	14.17	10.30	9.24	7.73	6.48	7.56	7.22	7.47
Fair	25.77	21.71	19.39	18.79	16.78	19.56	21.54	22.96
Good	30.91	32.31	31.61	30.99	30.61	30.16	31.16	30.95
Very good	21.38	26.41	28.11	28.95	32.23	30.46	29.36	26.92
Excellent	7.77	9.27	11.66	13.54	13.90	12.26	10.72	11.69
Retired (%)	95.46	91.47	77.30	64.98	59.33	50.21	43.15	34.91
Annual consumption ($1000s, mean)	22.48	24.99	25.02	26.25	26.81	23.39	19.98	18.18
Male (%)	37.48	46.86	45.03	45.27	37.45	42.39	42.40	39.56
Education (%)								
<HS	41.57	32.07	31.17	28.31	21.27	19.97	22.16	22.96
HS	29.71	31.79	32.93	33.13	31.11	24.74	25.19	24.30
Some College	16.45	17.86	18.58	20.45	24.40	28.46	29.71	28.75
College	12.27	18.28	17.32	18.11	23.23	26.82	22.93	23.99
Race (%)								
White	80.96	83.40	75.53	73.02	76.20	61.70	53.15	48.42
Black	12.93	9.74	16.45	16.09	15.07	21.65	26.64	28.41
Other	6.11	6.85	8.02	10.89	8.73	16.65	20.20	23.17

Notes: Children of the Depression denoted by CODA, War Babies by WB, early Baby Boomers by BB, and mid Baby Boomers by MBB. Consumption is reported in real 2010 dollars. Source: HRS.

We estimate each block in our model separately as there is no simultaneity across blocks. As shown in the methods section of the paper, the consumption and wealth blocks only consist of one equation which follows a standard linear dynamic panel data model with lagged dependent variables and fixed effects at the individual level. We estimate these equations with OLS, but to avoid the Nickell (1981) bias that OLS can generate for this kind of model, we use the Everaert and Pozzi (2007) bootstrap-based method.[1] By including a single period lag of retirement and health

[1] We implement the bootstrap with De Vos et al. (2015) Stata routine *xtbcfe*.

on consumption, and two lags of consumption on itself, we ensure that shocks are not serially correlated in the consumption equation. Similar lags are included in the wealth equation. We also use a VAR(2) system in the retirement, health, and survival equations to maintain consistency with the consumption and wealth models. The self-rated health equation is estimated independently of other VAR blocks via maximum likelihood, while the retirement and mortality equations are estimated independently using standard probit regressions.[2]

Finally, we estimate the morbidity block, which we model as a multivariate probit with correlated shocks. To estimate this model, we use a chain of bivariate probit estimators suggested by Mullahy (2016) because of the large number of outcomes and observations in the HRS. While this approach allows for consistent estimation via maximum likelihood, a potential issue arises due to the absorbing nature of morbidity states. This means, for example, diagnosed hypertension at time t perfectly predicts hypertension at time $t+1$ and we have quasi-complete separation. In a univariate probit model, we could condition on not being diagnosed with the morbidity at time t to solve this issue, but in the bivariate probit this is not possible. Thus, we constrain the infinite coefficients to large values in the bivariate probit, but this does not affect the likelihood or estimates of remaining (non-infinite) coefficients.

The full set of estimation results are shown in Tables 3-5.

B.3 Simulations

We used the estimated panel VAR model to construct the expected remaining lifetime utility for a subset of sixty-year-olds from the HRS. Analyses are limited to the EHRS, LHRS, War Babies, and early Baby Boomers cohorts as simulations require data at age fifty-eight and sixty as "initial" conditions. The HRS provides respondent-level analysis weights for each wave, designed to create representative cohort samples of the non-institutionalized US population. We used base year weights corresponding to when the cohort was approximately age sixty to analyze the welfare distribution. Specifically, we followed Miller and Bairoliya (2022) and used the 1996 analysis weights for the EHRS, 2000 for the LHRS, 2006 for War Babies, and 2008 for Baby Boomers. As any missing data was imputed among respondents, no individuals were removed from the simulation due to missing item response. However, individuals were removed if they were not surveyed at ages 58-59 and 60-61. For example, any EHRS cohort member interviewed at age 60 in 1996 but missing from the previous survey round would be excluded from the simulation sample but included in the 2000 nationally representative sample. Table 2 provides a comparison of time invariant characteristics between the weighted representative sample and the sample used in our simulations after dropping these missing cases. The simulation sample was slightly more female, educated, and white in comparison to the representative sample, but the differences were minor and generally consistent across all cohorts.

Using age sixty data as initial ($t=0$) conditions[3], we simulate the remaining life outcomes for each individual (i) as follows:

[2]There is no incidental parameters or initial conditions problem in these models as there is no permanent unobserved heterogeneity or serial correlation. The standard (ordered) probit estimator is consistent and provides asymptotically valid test statistics and standard errors.

[3]Initial conditions also include unobserved endowments $\hat{\pi}$ estimated using the prediction method of De Vos et al. (2015).

Table 2: Representative and simulation sample comparison

	EHRS		LHRS		WB		BB	
	Rep	Sim	Rep	Sim	Rep	Sim	Rep	Sim
	0	1	2	3	4	5	6	7
Individuals	3,096	3,029	3,816	3,541	2,628	2,506	2,911	2,640
Male (%)	47.16	46.33	46.71	46.54	47.93	47.93	48.26	47.56
Education (%)								
<HS	29.27	29.11	25.41	25.48	18.49	18.18	14.52	14.50
HS	33.82	33.97	32.34	32.61	30.65	30.52	25.07	25.17
Some College	19.27	19.27	21.56	21.36	24.26	24.37	29.19	28.95
College	17.64	17.64	20.69	20.54	26.60	26.93	31.23	31.37
Race (%)								
White	83.36	83.90	81.52	81.90	82.48	83.06	79.82	80.25
Black	10.55	10.42	10.16	10.10	9.64	9.14	11.07	10.85
Other	6.09	5.68	8.32	7.99	7.88	7.80	9.12	8.89

Notes: War Babies denoted by WB and Baby Boomers by BB. EHRS cohort inclues those under age 60 in 1992. "Rep" indicates representative sample based on HRS respondent analysis weights. "Sim" indicates simulation sample weighted by the same analysis weights.

1. Survival shock u_{i1} is drawn and survival to time $t = 1$ (age 62) is determined according to the mortality equation. If individual survives, move to step two.

2. Morbidity shock vector e_{i1} is drawn from a standard multivariate normal distribution with estimated covariance matrix Σ (see Table 5). This shock vector along with the model outlined in the methods section is used to compute simulated age 62 morbidity vector M_{i1}.

3. Given age 62 morbidities (M_{i1}), general health shock $\varepsilon_{2,i1}$ is drawn and age 62 self-rated health (s_{i1}) is computed.

4. Given age 62 self-rated health (s_{i1}) and morbidities (M_{i1}), retirement shock $\varepsilon_{3,i1}$ is drawn to determine age 62 retirement (r_{i1}).

5. Given age 62 retirement, self-rated health, and morbidities (r_{i1}, s_{i1}, M_{i1}), consumption shock $\varepsilon_{4,i1}$ is drawn to determine age 62 consumption (c_{i1}).[4]

6. Given all other age 62 outcomes $(c_{i1}, r_{i1}, s_{i1}, M_{i1})$, wealth shock $\varepsilon_{5,i1}$ is drawn to determine age 62 wealth (w_{i1}).

7. Steps 1-6 are repeated for $t = 2, 3, \ldots$ until death or $t = 30$ (age 120).

8. Steps 1-7 are repeated 5,000 times for each individual.

Figures 1-4 show a comparison between the average simulated life-cycle profiles and those constructed from available data by race for the EHRS cohort. The simulations closely match the

[4] ε_4 is drawn from the normal distribution with mean zero and standard deviation determined to match the empirical error distribution of each cohort. Specifically, standard deviations used for EHRS, LHRS, WB, and BB cohorts are 0.49, 0.48, 0.48, and 0.40. Clustering by cohort provides a slightly better fit to the data.

available aggregated data, indicating that our life-cycle dynamics model is a reasonable approximation of the underlying data generating processes. Note that the data and simulations are the same at age 60 by construction. However, the simulations match the data quite well even up to 24 years later, when the EHRS cohort reaches age 84.

To further demonstrate the accuracy of our model, we compare consumption and health utility means and standard deviations of the data with simulated life-cycle profiles for each birth cohort in Figures 5-6. The simulations match the data well across birth cohorts, further highlighting the advantages of using the VAR approach to forecast joint dynamics accurately.

B.4 Figures and Tables

Table 3: Model estimates for ADLs, self-rated health, retirement, consumption, and mortality

	ADLs		Self-rated health		Retirement		Consumption		Mortality	
Variable	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	SE	SE
Hyper			-0.271	0.014	0.078	0.036	-0.001	0.014	0.102	0.026
Diab			-0.254	0.018	0.064	0.046	-0.003	0.014	0.100	0.033
Cancer			-0.678	0.019	0.191	0.051	0.028	0.018	0.655	0.026
Lung			-0.464	0.023	0.142	0.069	-0.005	0.020	0.409	0.032
Heart			-0.485	0.016	0.127	0.045	-0.007	0.016	0.193	0.024
Stroke			-0.480	0.022	0.464	0.074	-0.070	0.024	0.243	0.029
Psych			-0.428	0.021	0.392	0.058	-0.051	0.019	0.239	0.029
Arthritis			-0.225	0.014	0.036	0.034	0.018	0.014	-0.023	0.024
ADL			-0.664	0.013	0.368	0.039	-0.060	0.017	0.334	0.019
Health 2					-0.578	0.046	0.049	0.022	-0.332	0.017
Health 3					-0.725	0.047	0.062	0.023	-0.544	0.019
Health 4					-0.741	0.049	0.086	0.023	-0.662	0.022
Health 5 (best)					-0.725	0.054	0.114	0.027	-0.652	0.032
Lag Hyper	0.037	0.031	0.147	0.019	-0.032	0.049	-0.005	0.012	-0.046	0.026
Lag Diab	0.080	0.039	0.084	0.025	-0.010	0.067	-0.003	0.015	0.070	0.034
Lag Cancer	0.028	0.043	0.524	0.028	-0.121	0.079	-0.007	0.015	-0.447	0.028
Lag Lung	0.163	0.049	0.198	0.033	0.007	0.104	-0.010	0.025	-0.120	0.034
Lag Heart	0.075	0.033	0.277	0.022	-0.162	0.068	0.003	0.016	-0.038	0.025
Lag Stroke	0.372	0.046	0.348	0.032	-0.253	0.123	-0.003	0.019	-0.053	0.032
Lag Psych	0.360	0.043	0.241	0.030	-0.141	0.087	0.025	0.018	-0.149	0.032
Lag Arthritis	0.210	0.026	0.115	0.018	0.051	0.045	-0.009	0.012	-0.080	0.023
Lag ADL			0.326	0.018	-0.170	0.057	0.005	0.014	-0.117	0.020
Lag Health 2	-0.229	0.030	0.621	0.014	0.012	0.061	0.012	0.012	-0.039	0.018
Lag Health 3	-0.470	0.031	1.120	0.015	-0.029	0.062	0.013	0.015	-0.078	0.020
Lag Health 4	-0.641	0.033	1.650	0.016	-0.064	0.064	0.014	0.015	-0.115	0.023
Lag Health 5	-0.722	0.040	2.272	0.018	-0.076	0.067	0.017	0.015	-0.148	0.031
Time	-0.049	0.007	0.019	0.003	-0.014	0.010	0.004	0.010	-0.014	0.005
2008+	0.030	0.025	0.011	0.012	-0.023	0.033	-0.044	0.009	0.045	0.021
CODA	0.102	0.031	0.021	0.016	0.092	0.078			-0.010	0.024
Early HRS	0.132	0.044	0.014	0.022	0.091	0.092			-0.047	0.033
Late HRS	0.138	0.057	0.004	0.028	0.014	0.106			-0.064	0.043
War Babies	0.168	0.071	-0.017	0.034	0.064	0.123			-0.116	0.055
Boomers	0.267	0.086	-0.087	0.042	0.040	0.145			-0.143	0.067
Mid Boomers	0.332	0.102	-0.135	0.050	-0.012	0.165			-0.199	0.083
Late Boomers	0.334	0.150	-0.147	0.070	-0.046	0.202			-0.088	0.161
Black	0.098	0.019	-0.066	0.009	0.054	0.023			0.042	0.016
Other race	0.062	0.024	-0.129	0.011	0.010	0.030			-0.169	0.022
Female	-0.011	0.014	0.036	0.007	0.118	0.017			-0.219	0.013
HS grad	-0.083	0.016	0.076	0.008	-0.026	0.023			0.027	0.014
Some college	-0.040	0.019	0.113	0.009	-0.046	0.025			0.009	0.017
College grad	-0.091	0.023	0.188	0.010	-0.052	0.028			-0.007	0.020
Retired							-0.041	0.011	0.202	0.032
Lag Retired	0.104	0.028	-0.026	0.013			-0.024	0.011	-0.022	0.028
Lag2 Retired	0.001	0.026	-0.015	0.012						
Lag Con							0.170	0.005		
Lag2 Con							0.081	0.005		
Constant	-0.927	0.077			-0.849	0.184			-1.763	0.249

Notes: Dependent variable across columns. Multivariate probit results reported for ADLs as dependent outcome. Standard (ordered) probit results reported for self-rated health, mortality, and retirement as dependant outcomes. Linear dynamic panel estimates reported for consumption as outcome. All regressions also include dummies for age. Regressions for ADLs, self-rated health, mortality, and retirement also include dummies for occupation and census division. Regressions for ADLs and self-rated health also includes second lag for all health outcomes.

Table 4: Model estimates for morbidities

	Hypertension		Diabetes		Cancer		Lung disease		Heart disease		Stroke		Psych		Arthritis	
Variable	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	SE	SE
Lag Hyper			0.251	0.034	-0.027	0.038	0.087	0.040	0.125	0.033	0.106	0.040	0.143	0.037	0.071	0.033
Lag Diab	0.248	0.050			0.066	0.046	0.052	0.050	0.052	0.043	0.039	0.052	0.027	0.050	0.062	0.044
Lag Cancer	-0.037	0.051	0.015	0.053			0.039	0.058	-0.083	0.049	-0.030	0.058	-0.043	0.059	0.055	0.050
Lag Lung	0.110	0.058	0.093	0.056	0.084	0.058			0.263	0.051	0.018	0.062	0.100	0.062	0.155	0.065
Lag Heart	0.098	0.043	0.085	0.040	0.007	0.041	0.204	0.040			0.172	0.040	0.064	0.041	0.080	0.042
Lag Stroke	0.082	0.066	-0.046	0.063	-0.013	0.057	-0.020	0.062	0.069	0.053			0.256	0.051	-0.040	0.062
Lag Psych	0.053	0.055	0.070	0.051	-0.055	0.058	0.087	0.056	0.083	0.047	0.154	0.053			0.270	0.054
Lag Arthritis	0.085	0.029	-0.006	0.033	-0.012	0.034	0.139	0.036	0.068	0.030	-0.002	0.036	0.117	0.035		
Lag ADL	0.057	0.033	0.029	0.034	0.017	0.034	0.080	0.036	0.075	0.030	0.180	0.032	0.209	0.032	0.167	0.036
Lag Health 2	0.011	0.035	0.001	0.032	-0.045	0.034	-0.069	0.032	-0.101	0.030	-0.122	0.032	-0.207	0.031	-0.070	0.037
Lag Health 3	0.004	0.036	-0.009	0.034	-0.075	0.036	-0.147	0.035	-0.164	0.031	-0.210	0.034	-0.296	0.033	-0.108	0.038
Lag Health 4	-0.036	0.038	-0.083	0.037	-0.106	0.038	-0.305	0.040	-0.250	0.034	-0.240	0.038	-0.388	0.038	-0.152	0.040
Lag Health 5 (best)	-0.119	0.042	-0.215	0.045	-0.139	0.045	-0.442	0.055	-0.291	0.040	-0.362	0.050	-0.476	0.050	-0.245	0.044
Lag2 Hyper			0.039	0.033	0.056	0.038	-0.091	0.040	0.049	0.032	0.036	0.040	-0.087	0.037	0.031	0.033
Lag2 Diab	-0.086	0.053			-0.068	0.049	-0.122	0.053	0.105	0.045	0.087	0.054	-0.008	0.052	-0.056	0.047
Lag2 Cancer	0.018	0.055	-0.011	0.057			0.043	0.061	0.075	0.053	-0.005	0.061	0.061	0.063	-0.014	0.054
Lag2 Lung	-0.167	0.064	-0.073	0.061	0.044	0.063			-0.124	0.056	0.036	0.067	0.019	0.067	-0.077	0.072
Lag2 Heart	-0.049	0.046	0.018	0.042	0.014	0.043	-0.091	0.042			-0.026	0.041	-0.056	0.043	-0.019	0.044
Lag2 Stroke	-0.025	0.075	0.073	0.069	0.002	0.063	0.038	0.068	0.053	0.059			-0.165	0.058	0.026	0.069
Lag2 Psych	-0.019	0.058	-0.063	0.055	0.056	0.061	0.051	0.059	-0.019	0.050	-0.041	0.056			-0.131	0.058
Lag2 Arthre	-0.040	0.030	0.000	0.033	0.049	0.034	-0.044	0.035	0.024	0.029	-0.021	0.036	-0.020	0.034		
Lag2 ADL	-0.060	0.035	0.037	0.036	-0.019	0.036	0.003	0.037	0.005	0.031	-0.093	0.034	-0.061	0.034	-0.055	0.041
Lag2 Health 2	-0.018	0.037	-0.075	0.033	-0.041	0.036	-0.089	0.034	0.008	0.032	-0.055	0.034	-0.069	0.033	0.054	0.041
Lag2 Health 3	-0.019	0.037	-0.070	0.035	-0.009	0.037	-0.144	0.036	-0.015	0.034	-0.065	0.037	-0.115	0.035	0.068	0.042
Lag2 Health 4	-0.033	0.039	-0.113	0.038	-0.002	0.040	-0.197	0.040	-0.043	0.036	-0.053	0.040	-0.203	0.039	0.032	0.043
Lag2 Health 5	-0.060	0.042	-0.143	0.044	0.001	0.045	-0.292	0.052	-0.089	0.041	-0.096	0.048	-0.264	0.049	-0.036	0.047
Time	0.039	0.007	0.029	0.008	0.005	0.008	0.013	0.009	-0.003	0.007	-0.023	0.008	0.006	0.008	-0.033	0.007
2008+	-0.061	0.028	-0.063	0.030	0.015	0.030	-0.015	0.034	-0.047	0.026	0.013	0.032	-0.108	0.033	0.021	0.028
CODA	-0.031	0.038	-0.036	0.042	-0.019	0.039	0.016	0.044	-0.015	0.035	0.017	0.039	0.075	0.042	-0.097	0.038
Early HRS	-0.084	0.053	-0.072	0.058	-0.075	0.054	-0.036	0.062	0.013	0.048	0.004	0.054	0.073	0.058	-0.097	0.053
Late HRS	-0.083	0.066	-0.082	0.073	-0.094	0.069	0.020	0.079	0.042	0.062	0.014	0.069	0.113	0.074	0.004	0.067
War Babies	-0.093	0.082	-0.038	0.090	-0.072	0.086	0.014	0.099	0.059	0.076	0.087	0.087	0.236	0.090	0.121	0.082
Boomers	-0.175	0.100	-0.027	0.110	-0.119	0.106	0.005	0.121	0.103	0.093	0.079	0.106	0.326	0.110	0.166	0.100
Mid Boomers	-0.307	0.118	-0.013	0.129	-0.090	0.127	0.069	0.144	0.126	0.112	0.145	0.128	0.313	0.130	0.200	0.118
Late Boomers	-0.309	0.159	0.117	0.167	-0.208	0.204	0.002	0.220	0.130	0.167	0.479	0.202	0.038	0.200	0.245	0.156
Black	0.197	0.022	0.118	0.021	-0.049	0.022	-0.185	0.026	-0.157	0.020	0.036	0.024	-0.199	0.025	-0.020	0.021
Other race	0.100	0.025	0.260	0.025	-0.200	0.032	-0.282	0.035	-0.218	0.027	-0.117	0.033	-0.017	0.030	-0.105	0.026
Female	0.015	0.015	-0.108	0.017	-0.196	0.017	-0.039	0.020	-0.173	0.015	-0.064	0.019	0.128	0.019	0.161	0.015
HS grad	-0.030	0.019	-0.056	0.020	-0.013	0.020	-0.108	0.022	0.005	0.018	0.035	0.022	-0.065	0.022	-0.046	0.020
Some college	-0.066	0.021	-0.061	0.023	0.026	0.023	-0.110	0.026	0.021	0.021	0.044	0.026	0.000	0.025	-0.010	0.022
College grad	-0.106	0.024	-0.120	0.027	0.033	0.027	-0.226	0.032	-0.053	0.024	0.033	0.030	-0.040	0.030	-0.044	0.024
Lag Retired	-0.036	0.030	0.050	0.031	0.030	0.034	0.057	0.041	0.005	0.031	0.048	0.043	0.085	0.038	0.003	0.029
Lag2 Retired	0.021	0.029	-0.047	0.030	-0.004	0.032	0.004	0.038	0.004	0.030	0.033	0.039	-0.033	0.036	-0.022	0.028
Constant	-1.549	0.086	-2.027	0.093	-1.908	0.093	-2.015	0.107	-1.726	0.084	-2.506	0.112	-1.866	0.097	-1.311	0.087

Notes: Multivarite probit results with dependent variable across columns. Regressions also include dummies for age, occupation, and census division.

Table 5: Morbidity shock covariance matrix (Σ)

	Hyper	Diabetes	Cancer	Lung	Heart	Stroke	Psych	Arthritis	ADLs
Hyper	1.00	0.27	0.05	0.09	0.28	0.29	0.14	0.09	0.11
Diabetes	0.27	1.00	0.06	0.06	0.10	0.14	0.08	0.04	0.07
Cancer	0.05	0.06	1.00	0.13	0.04	0.06	0.12	0.06	0.13
Lung	0.09	0.06	0.13	1.00	0.23	0.11	0.18	0.08	0.19
Heart	0.28	0.10	0.04	0.23	1.00	0.28	0.16	0.09	0.14
Stroke	0.29	0.14	0.06	0.11	0.28	1.00	0.21	0.11	0.40
Psych	0.14	0.08	0.12	0.18	0.16	0.21	1.00	0.16	0.29
Arthritis	0.09	0.04	0.06	0.08	0.09	0.11	0.16	1.00	0.26
ADLs	0.11	0.07	0.13	0.19	0.14	0.40	0.29	0.26	1.00

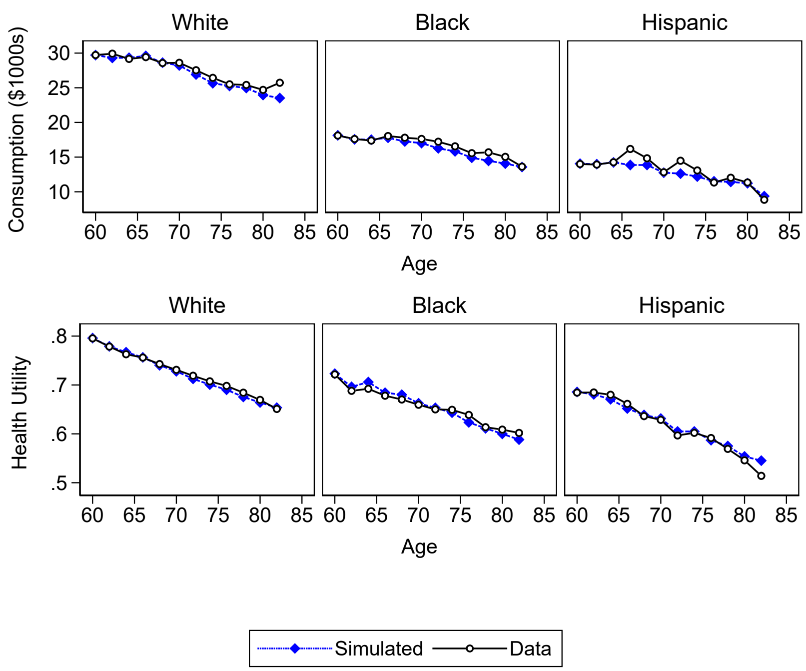

Figure 1: Mean of life-cycle consumption and health utility profiles by race/ethnicity

Notes: "Data" plots mean of all available data (inclusive of imputed missing values) in the EHRS cohort by two-year age interval. "Simulated" plots mean of expected simulated outcome for each observation in the data (i.e. the expected outcome for each person-year observation in the data).

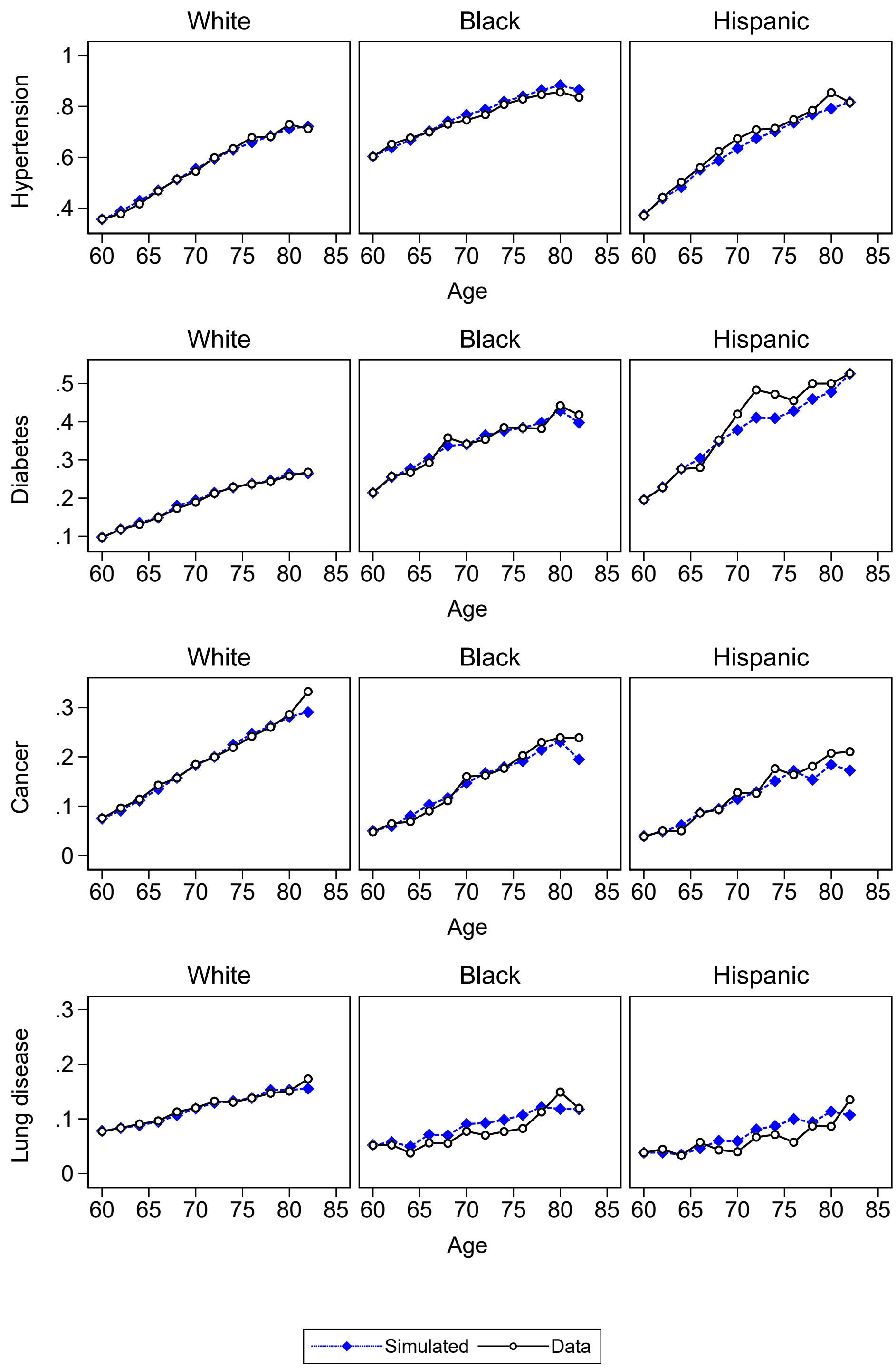

Figure 2: Mean of life-cycle morbidity profiles by race/ethnicity

Notes: "Data" plots mean of all available data (inclusive of imputed missing values) in the EHRS cohort by two-year age interval. "Simulated" plots mean of expected simulated outcome for each observation in the data (i.e. the expected outcome for each person-year observation in the data).

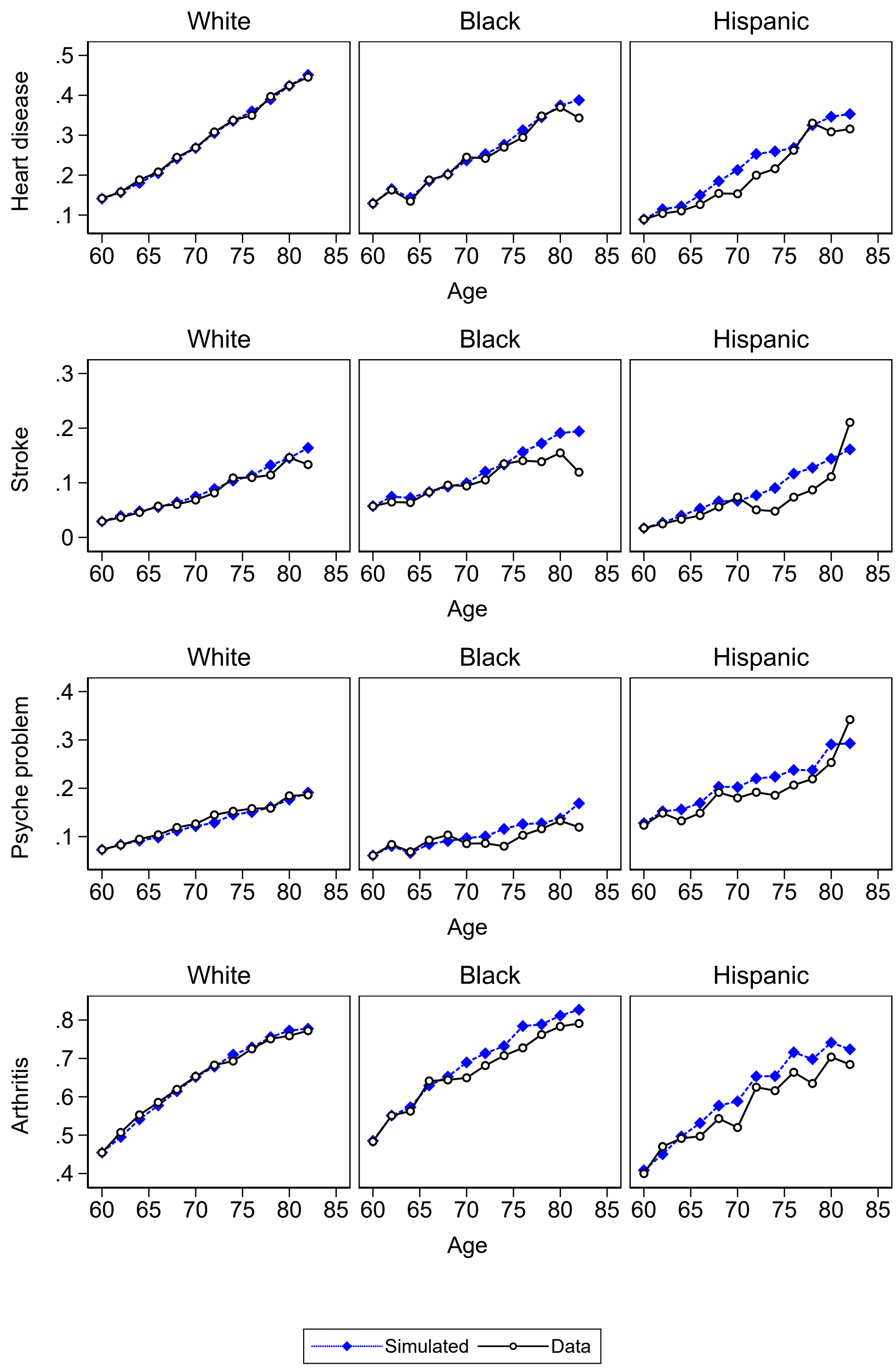

Figure 3: Mean of life-cycle morbidity profiles by race/ethnicity

Notes: "Data" plots mean of all available data (inclusive of imputed missing values) in the EHRS cohort by two-year age interval. "Simulated" plots mean of expected simulated outcome for each observation in the data (i.e. the expected outcome for each person-year observation in the data).

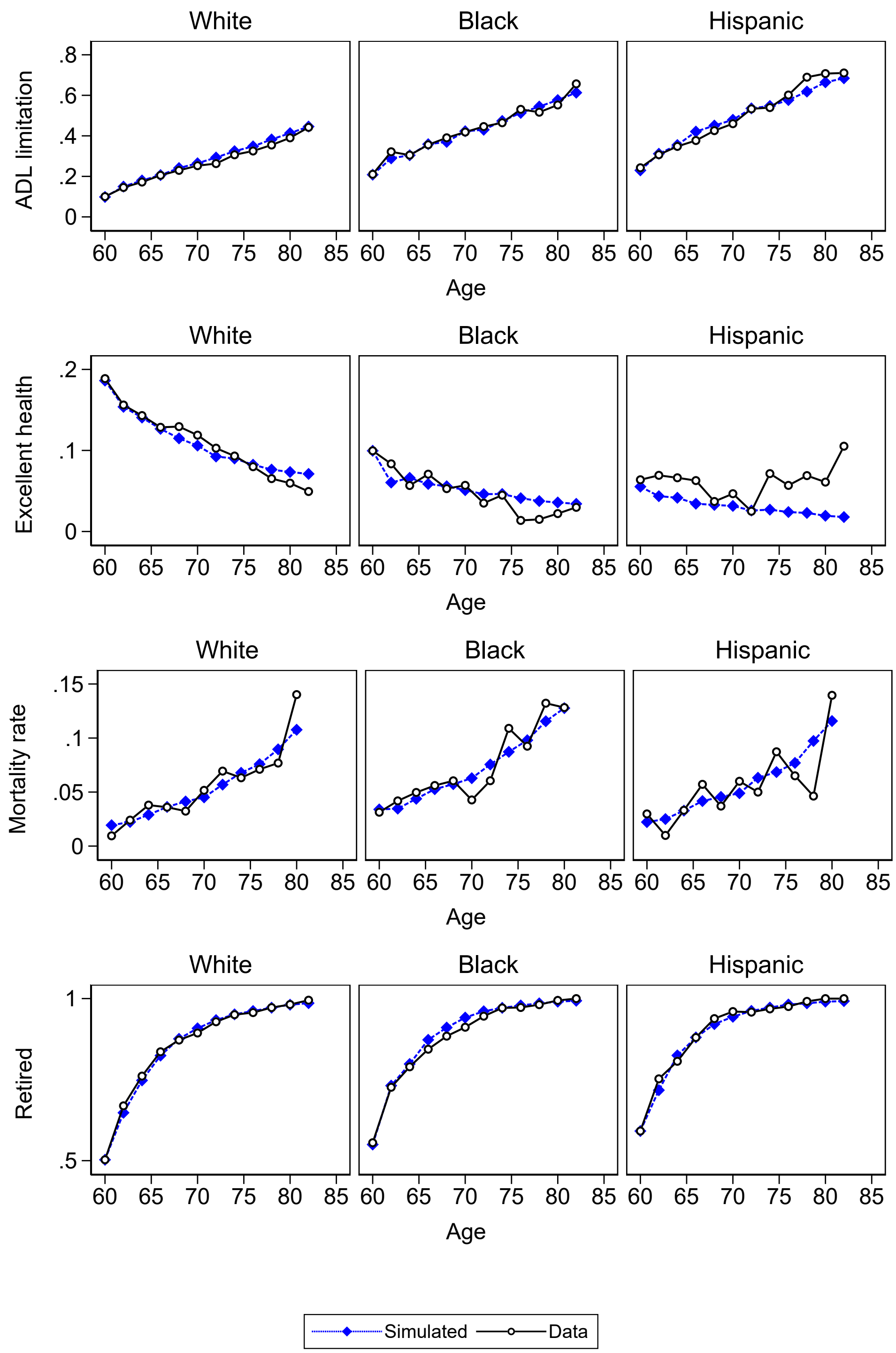

Figure 4: Mean of life-cycle health, mortality, and retirement profiles by race/ethnicity

Notes: "Data" plots mean of all available data (inclusive of imputed missing values) in the EHRS cohort by two-year age interval. "Simulated" plots mean of expected simulated outcome for each observation in the data (i.e. the expected outcome for each person-year observation in the data).

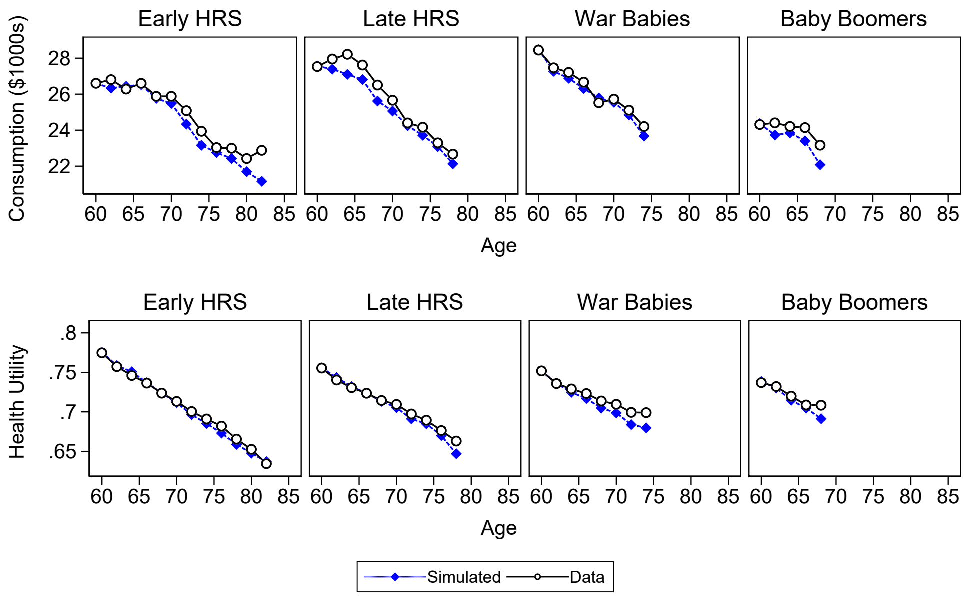

Figure 5: Mean of life-cycle consumption and health utility profiles by cohort

Notes: "Data" plots mean of all available data (inclusive of imputed missing values) in HRS by two-year age interval and cohort. "Simulated" plots mean of expected simulated outcome for each observation in the data (i.e. the expected outcome for each person-year observation in the data).

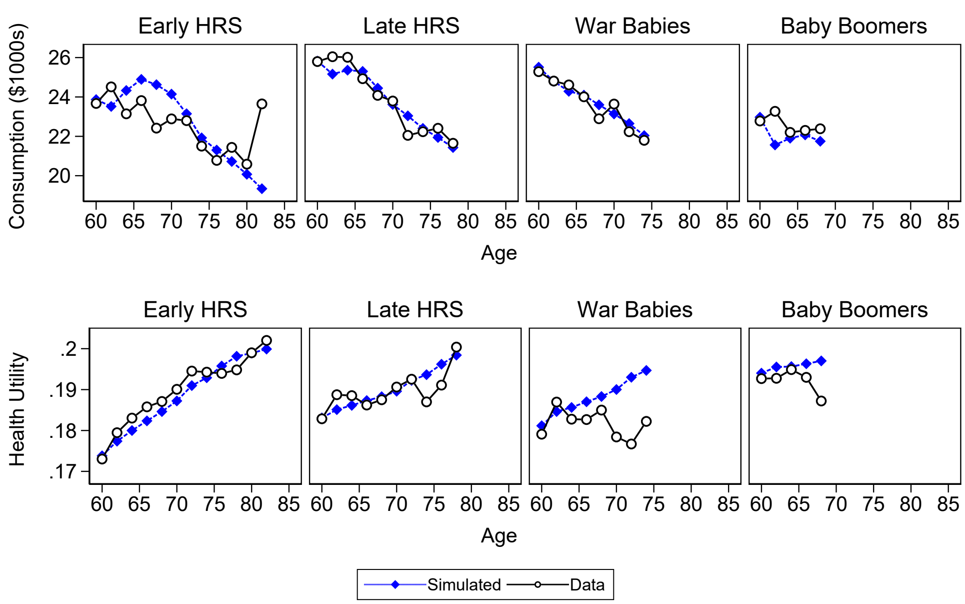

Figure 6: Standard deviation of consumption and health utility life-cycle profiles by cohort

Notes: "Data" plots standard deviation of all available data (inclusive of imputed missing values) in HRS by two-year age interval and cohort. "Simulated" plots mean of standard deviations of simulated outcome (i.e. the mean of standard deviations calculated for each of the 5,000 simulation runs).

C Health utility weights

We obtain our health utility weights ω from the Health Utilities Index Mark 3 (HUI3) instrument, which was administered to around 1,200 participants in the HRS in 2000. The HUI3 instrument was designed to produce cardinal utility scores on the standard utility scale of 0 (death) to 1 (best health) and has been widely used in studies on health utilities (Furlong et al., 1998; Feeny et al., 2002; Horsman et al., 2003). We use the HUI multi-attribute utility score (*hui3ou*) for our analysis.

The HUI3 was conceptualized such that $u(h_i) = HUI3_i \times u(h_{best})$ for individual i and general utility function $u(.)$, where h_{best} refers to the best possible health state. For example, a year in the best health state is equivalent in utility to two years with $HUI3 = 0.5$. For our model, we adopt the approach of Miller and Bairoliya (2022) and assume that the HUI3 measures relative utility across health states *while holding consumption and leisure fixed*:

$$\omega h_i \left[\bar{u} + log\left(c_i\right) + \nu\left(l_i\right)\right] = HUI3_i \times h_{best}\left[\bar{u} + log\left(c_i\right) + \nu\left(l_i\right)\right].$$

This approach is consistent with the HUI3 instrument, as the interview script instructs participants to imagine themselves in the given health states while assuming that where they live, their income, and their friends and family remain constant. Given this assumption, the above equation simplifies to $\omega h_i = HUI3_i$ when $h_{best} = 1$. We estimate the utility weights ω by regressing the HUI3 utility score on self-rated health and all morbidity indicators. Estimated benchmark health utility weights are presented in Table 6.

Table 6: Estimated health utility weights (γ)

Measure	Weight	SE
Self-rated health		
Fair	0.229	0.026
Good	0.314	0.026
Very good	0.406	0.027
Excellent	0.421	0.031
Hypertension	0.003	0.012
Diabetes	-0.003	0.018
Cancer	0.009	0.017
Lung disease	-0.027	0.022
Heart disease	-0.031	0.015
Stroke	-0.077	0.022
Psych problem	-0.070	0.020
Arthritis	-0.062	0.013
Diff with ADL	-0.158	0.017
Constant	0.516	0.028

Notes: Results from regression of adjusted HUI3 score on self-rated health and morbidities. SE denotes standard error. $R^2 = 0.17$. N = 760.

While this approach is consistent with the interview instructions of the survey, other researchers have questioned whether respondents are fully capable of conceptualizing changes in health states without also considering changes in other aspects of life (Feeny et al., 2018). For instance, respondents may have considered changes in consumption and leisure along with changes in health. In such cases, the appropriate representation of the HUI3 instrument would be as follows:

$$\gamma h\left[\bar{u} + log\left(c\right) + \nu\left(l\right)\right] = HUI3 \times h_{best}\left[\bar{u} + log\left(c_{best}\right) + \nu\left(l_{best}\right)\right].$$

Rearranging terms and setting $h_{best} = 1$ yields:

$$\gamma h = HUI3 \frac{\bar{u} + log\left(c_{best}\right) + \nu\left(l_{best}\right)}{\bar{u} + log\left(c\right) + \nu\left(l\right)}. \tag{1}$$

However, Miller and Bairoliya (2022) note that this formulation poses a problem because we do not observe the counterfactual consumption and leisure bundles that would be realized in the best health state. Nevertheless, we have already developed an independent forecasting model that enables us to predict the expected value for c_{best} and l_{best} for each individual in the sample. Armed with these predictions, we calculated the right-hand side of (1) for each HUI3 respondent. We then regressed this value on self-rated health and all morbidity indicators to obtain alternate utility weights γ (see results in Table 7). We used these alternative utility weights in our robustness exercises.

Table 7: Estimated alternate health utility weights (γ)

Measure	Weight	SE
Self-rated health		
Fair	0.263	0.040
Good	0.328	0.039
Very good	0.413	0.041
Excellent	0.401	0.046
Hypertension	-0.002	0.018
Diabetes	0.012	0.025
Cancer	0.004	0.024
Lung disease	-0.036	0.031
Heart disease	-0.047	0.022
Stroke	-0.048	0.031
Psych problem	-0.061	0.029
Arthritis	-0.057	0.020
Diff with ADL	-0.132	0.024
Constant	0.507	0.041

Notes: Results from regression of adjusted HUI3 score on self-rated health and morbidities. SE denotes standard error. $R^2 = 0.17$. N = 760.

D Additional welfare results

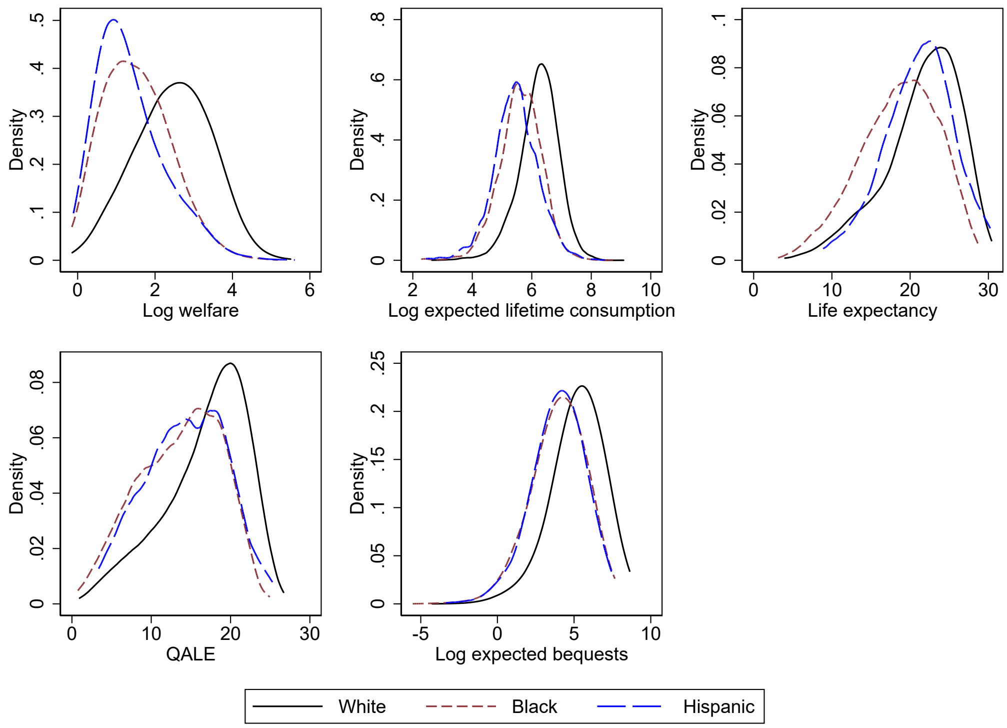

Figure 7: Distribution of welfare, consumption, and life expectancy by race

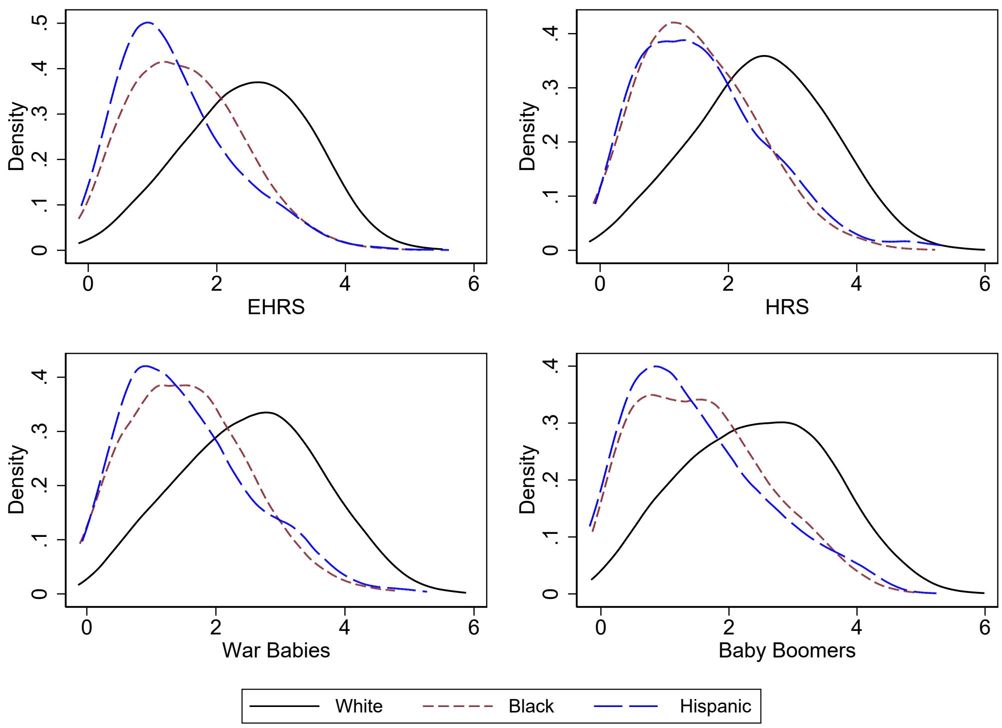

Figure 8: Distribution of log welfare by race and cohort

References

De Vos, I., Everaert, G., Ruyssen, I., et al. (2015). Bootstrap-based bias correction and inference for dynamic panels with fixed effects. *Stata Journal*, 15(4):986–1018(33).

Everaert, G. and Pozzi, L. (2007). Bootstrap-based bias correction for dynamic panels. *Journal of Economic Dynamics and Control*, 31(4):1160–1184.

Feeny, D., Furlong, W., and Torrance, G. W. (2018). What were they thinking when providing preference measurements for generic health states? the evidence for hui3. *Health and quality of life outcomes*, 16(1):166.

Feeny, D., Furlong, W., Torrance, G. W., Goldsmith, C. H., Zhu, Z., DePauw, S., Denton, M., and Boyle, M. (2002). Multiattribute and single-attribute utility functions for the health utilities index mark 3 system. *Medical care*, 40(2):113–128.

Furlong, W., Feeny, D., Torrance, G., Goldsmith, C., DePauw, S., Zhu, Z., Denton, M., Boyle, M., et al. (1998). Multiplicative multi-attribute utility function for the health utilities index mark 3 (hui3) system: a technical report. Technical report, Centre for Health Economics and Policy Analysis (CHEPA), McMaster University, Hamilton, Canada.

Honaker, J. and King, G. (2010). What to do about missing values in time-series cross-section data. *American Journal of Political Science*, 54(2):561–581.

Honaker, J., King, G., Blackwell, M., et al. (2011). Amelia II: A program for missing data. *Journal of Statistical Software*, 45(7):1–47.

Horsman, J., Furlong, W., Feeny, D., and Torrance, G. (2003). The health utilities index (hui®): concepts, measurement properties and applications. *Health and Quality of Life Outcomes*, 1(1):54.

Miller, R. and Bairoliya, N. (2022). Health, longevity, and welfare inequality of older americans. *(Forthcoming) The Review of Economics and Statistics*.

Mullahy, J. (2016). Estimation of multivariate probit models via bivariate probit. *Stata Journal*, 16(1):37–51.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49(6):1417–1426.