Online Appendix for: "The Welfare Cost of Late-life Depression"

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A Imputation of consumption and other missing data

The CAMS collected consumption data for approximately 20% of the HRS sample starting from 2001. In order to estimate our dynamic panel models and construct simulated life-cycle paths for the remaining sample, we follow Miller et al. (2019) and Miller and Bairoliya (2022) and multiply impute the missing consumption data. We use the computationally attractive EM-bootstrapping algorithm allowing for cross-sectional time-series data proposed by Honaker and King (2010) and implemented through the freely available Amelia II software program (Honaker et al., 2011). This approach provides m separate complete datasets in which all analyses are conducted independently. Results are then combined into a single estimate.[1] We follow Miller and Bairoliya (2022) and set $m = 12$.

There are two primary assumptions underlying the proposed imputation method. First, the complete data is assumed to be multivariate normal. While this may seem somewhat restrictive, it has been shown that multivariate normal imputation models provide an adequate approximation to the true underlying distribution in a variety of settings, even in the presence of categorical or mixed data (Schafer, 1997). Second is the standard required assumption that data is missing at random (MAR)—any nonrandom pattern of missingness can be accounted for by the observed data included in the model. Note this is less restrictive than the requirement data be missing completely at random (MCAR). In practice, we know that missing data is not at random, at least for years falling outside of the CAMS window (1992-1998 and 2016). However, by including a rich set of related covariates in the imputation model, we argue that missing data can be treated as MAR in the statistical sense. While there is no way to empirically test this assumption, we run a number of diagnostic tests to check the credibility of the imputation model in search of any obvious deficiencies.

Variables from the RAND HRS Longitudinal File 2016 (V2) included in our imputation model are number of household members (HHRES), age (AGEY_E), aged squared, cubed root of total wealth (ATOTA), log household income (ITOT)[2], and dummy indicators for cohort (COHBYR), labor force status (LBRF), gender (RAGENDER), race (RARACEM), education (RAEDUC), marital status (MSTAT), census division (CENDIV), 1980 census occupation code for longest reported tenure (JLOCC)[3], CESD score (CESD), self-reported health (SHLT), ADLs (ADLA), and eight doctor diagnosed health conditions (HIBPE, DIABE, CANCRE, LUNGE, HEARTE, STROKE, PSYCHE, ARTHRE). The model also included our constructed indicator for retirement and hours worked. In order to allow for the time-series structure of the data, lags and leads of consumption, wealth, income, and hours worked are included in the imputation model. While we are primarily imputing consumption data, Amelia II also provides imputed values for all other missing variables included in the model.[4]

A useful check of the viability of the imputation model is to compare the distributions of the imputed values against the observed data. While there is no need for these distributions to be the

[1] Assuming asymptotically normally distributed statistics implies a simple average across datasets (Rubin, 2004).

[2] Transformed wealth bounded at values of -4 and 16 and log income bounded above at a value of 6. Both variables in thousands of 2010 dollars.

[3] We treat missing and "other" occupations as one category.

[4] If the observed data used in the imputation model has a poorly behaved likelihood, the convergence of the EM algorithm could be sensitive to the staring values chosen. We found no evidence of local convergence issues using the overdispersed start values diagnostic test proposed by Honaker et al. (2011).

same, the comparison gives a sense of the plausibility of imputations (Honaker et al., 2011). Figure 1 plots the density of observed and imputed values of consumption. The imputed values are taken as the mean across the *m* imputed datasets. The comparison suggests no unusual pattern in the distribution of imputed values, providing cursory support of model plausibility.

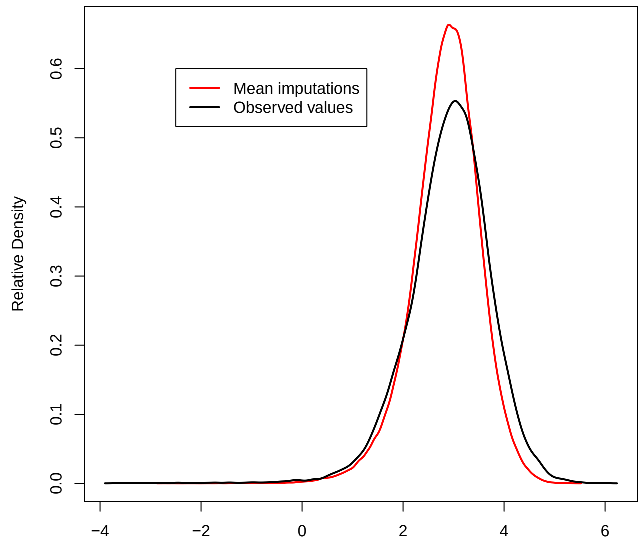

Figure 1: Distributions of observed and imputed values of consumption

Another diagnostic tool proposed by Honaker et al. (2011) is *overimputing*. While it is impossible to examine if the imputed values are close to the missing values they are attempting to recover, *observed* values can be used to test the accuracy of the imputation process. Overimputing sequentially treats each of the observed consumption values as if they were missing and then imputes their values several hundred times. This provides a mean imputed value and confidence interval that can be compared to the actual observed data. Figure 2 plots all observed consumption values against the mean of their imputed values and the associated 95% confidence interval. A visual inspection of the diagnostic plot suggests the model does fairly well predicting values other than the lowest values. However, few individuals lie in this extreme end of the distribution—less than 0.3% of the observations fall below zero ($1,000 annual consumption). Honaker et al. (2011) suggest a good imputation model should have at least 90% of the confidence intervals containing the true values (i.e. 90% of the confidence intervals should cross the $y = x$ line). In our case, 94% of the observed values are within the confidence bounds.

As a final examination of the imputation model we try to get a sense of how it predicts missing values in a time series. While it is infeasible to examine the imputed time trends for each individual in the sample, Figure 3 provides time series for a random sub-set of ten individuals with at least one observed consumption value. The mean of the imputed values are plotted in red with 95% confidence bounds (based on 100 imputations). The isolated black points without bounds are observed data. Broadly, the imputed values fall in line with the observed data and no egregious outliers emerge. Note that prior to wave five (2000) and for wave thirteen (2016) all values are

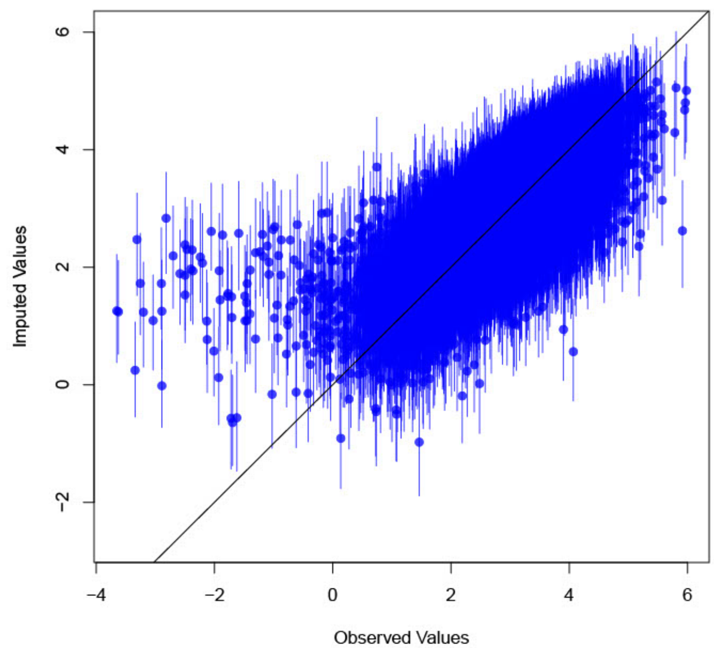

Figure 2: Overimputed values of consumption

imputed as these waves are outside of our CAMS data window.

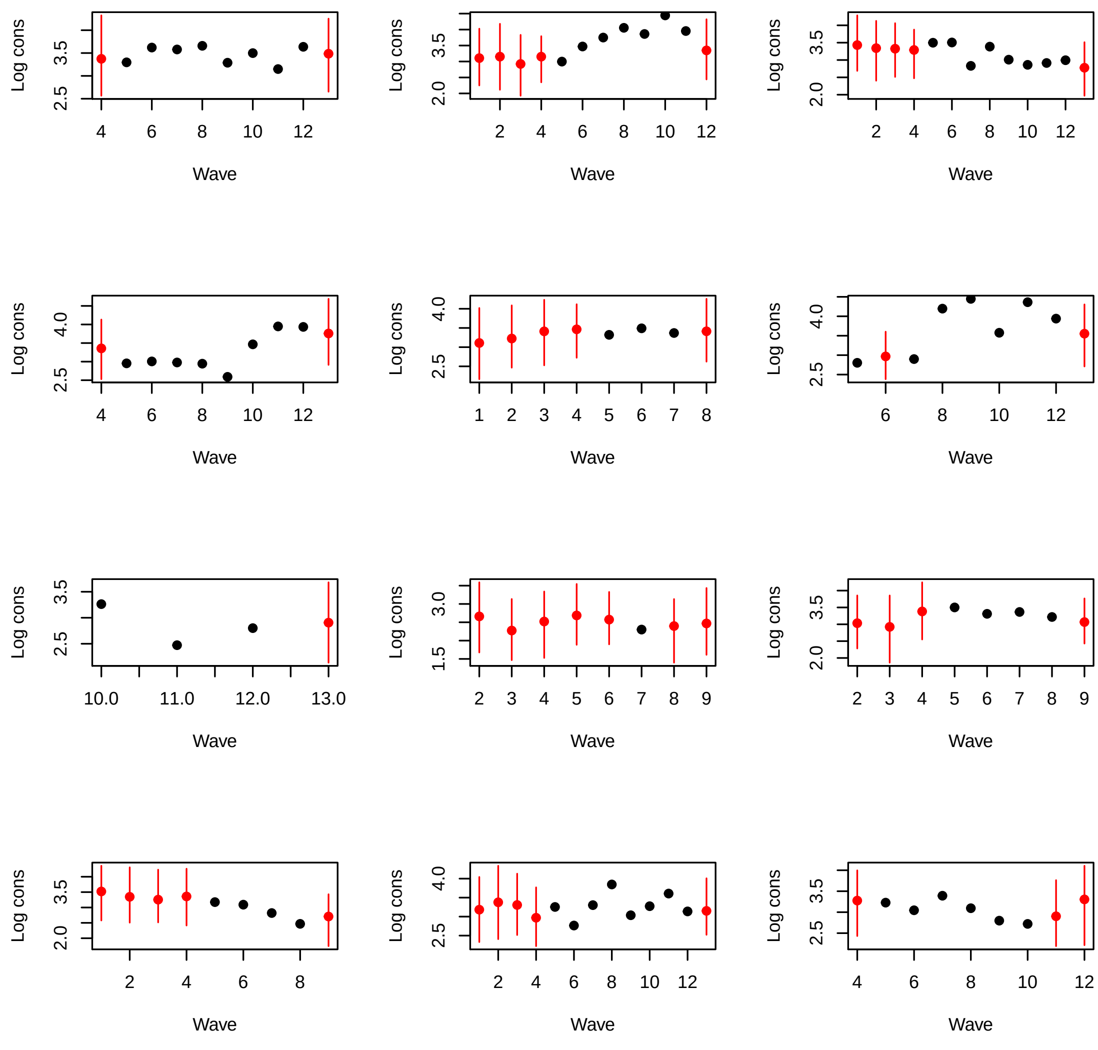

Figure 3: Observed and imputed consumption over time for a random sub-sample

B Simulation model

In this appendix we provide additional detail of our estimation and simulation procedures. For additional applications of this framework see Miller et al. (2019); Miller and Bairoliya (2022). As the HRS is collected biennially, a model period corresponds to two calendar years and individuals are grouped in two-year age intervals.

B.1 Higher order lags

Including additional outcome lags may be necessary to ensure there is no autocorrelation in the structural error terms of the system. The VAR(1) model extends easily to higher orders. For example, a VAR(2) version of our model takes the following form:

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

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

$$\left[\begin{array}{c:cccc} D_{11} & D_{12} & D_{13} & D_{14} & D_{15} \\ \hdashline D_{21} & d_{22} & d_{23} & d_{24} & d_{25} \\ D_{31} & d_{32} & d_{33} & d_{34} & d_{35} \\ D_{41} & d_{42} & d_{43} & d_{44} & d_{45} \\ D_{51} & d_{52} & d_{53} & d_{54} & d_{55} \end{array}\right] \left[\begin{array}{c} M_{it-2} \\ \hdashline s_{it-2} \\ d_{it-1} \\ r_{it-2} \\ c_{it-2} \end{array}\right].$$

Here, for example, coefficient vector D_{31} allows the second lag of the morbidity state vector to directly affect current depression. Note that it is not strictly required that the number of lags included be identical for each outcome. For example, excluding the second lag of self-rated health on consumption simply implies setting $d_{52} = 0$.

B.2 Estimation

The pooled sample used to estimate the simulation model includes all individuals born prior to 1960 and aged fifty and over at the time of the survey. This consists of 40,708 unique individuals and 238,091 total individual-year observations. Table 1 shows descriptive statistics for modeled outcomes for each cohort in the HRS. Prevalence of depressive symptoms was substantial among respondents, allowing for relatively precise estimates of their effects on dynamic processes. The share of observations reporting no depressive symptoms (CESD = 0) ranged from nearly 48% among War Babies to 33% among the oldest AHEAD cohort. The most severe depression state (CESD = 8) ranged from 1% in the EHRS cohort to 2.44% among mid-Baby Boomers. There was also substantial variation across diagnosed morbidities and reported self-rated health. In terms of labor supply, the share of retired individuals ranged from 34% in the most recent Baby Boomer cohort to 95% in the (much older) AHEAD cohort. Annual real consumption averaged between \$19-\$27,000 across cohorts. Younger cohorts were also more educated and racially diverse.

B.2.1 Methods

As there is no simultaneity across blocks in the system, we follow Miller and Bairoliya (2022) and estimate the model block-by-block. The consumption block is comprised only of equation (6), which is a standard single equation linear dynamic panel data model with lagged dependent variables and individual level fixed effects. The equation is estimated via OLS. We use the bootstrap-based method of Everaert and Pozzi (2007) to correct for the so-called Nickell (1981) bias that is known to arise from OLS estimates of such models.[5] Including a single period lag (two calendar years) of retirement and health on consumption and two lags (four years) for consumption on itself is sufficient to ensure that shocks are serially uncorrelated in the consumption equation.[6]

For consistency with the model of consumption, we use two lags of outcomes in all retirement, depression, health, and survival equations (i.e. we estimate a VAR(2) system and set $K = 2$ in the survival model). The ordered probit modes of self-rated health (3) and depression (4) are each estimated independently of other VAR blocks using maximum likelihood.[7] The retirement equation (5) and mortality equation (7) are estimated independently using standard probit regressions.

This leaves the morbidity block. The morbidity model (2) is structured as a multivariate probit with correlated shocks. Note that this approach does not allow for identification of the variance in structural errors in vector ε_1, but only of the variance in composite errors in vector e. Thus, while this approach is not sufficient for evaluating outcome responses to structural morbidity shocks, identification of composite errors is sufficient for forecasting outcomes as desired in our analysis. We follow Miller and Bairoliya (2022) and estimate this model using a chain of bivariate probit estimators as proposed by Mullahy (2016) due to the large number of outcomes and large number of observations in the HRS. With no additional assumptions, this approach allows for consistent estimation via maximum likelihood as opposed to relying on more computationally intensive simulation based methods. However, a potential estimation issue arises in the morbidity block because morbidity states are absorbing (e.g. *ever* been diagnosed with heart disease). This means, for example, diagnosed heart disease at time t perfectly predicts heart disease at time $t+1$ and we have quasi-complete separation. This implies the effective coefficients on the lagged dependent variables in the morbidity block are infinity (i.e. $\hat{b}_{11}, \hat{b}_{22}, \ldots, \hat{b}_{nn} = \infty$ in system (2)). In a simple univariate probit model, the obvious solution is to condition on not being diagnosed with the morbidity at time t. However, estimation of the bivariate probit involves maximization of the joint likelihood function, so the model is estimated while exogenously constraining infinite coefficients to large values ($\hat{b}_{11}, \hat{b}_{22}, \ldots, \hat{b}_{nn} = 10$), instead of conditioning on time t morbidity status. This restriction to include all observations in the bivariate probit does not effect the likelihood or estimates of the remaining (non-infinite) coefficients. For example, conditioning the bivariate probit

[5] We implement the bootstrap with De Vos et al. (2015) Stata routine $xtbcfe$. We use the deterministic initialization as our benchmark where initial conditions are set equal to those observed.

[6] Following Miller and Bairoliya (2022), we exclude second lags of retirement and health outcomes (included depression) as they were insignificant and noisy. This is equivalent to estimating the VAR(2) system with $D_{51} = d_{52} = d_{53} = d_{54} = 0$. First order autocorrelation was tested for consumption using the approach of Born and Breitung (2016) and implemented in Stata with Wursten et al. (2016). Under the null hypothesis of no autocorrelation, p-values were all greater than 0.22 regardless of imputed dataset used for the test.

[7] Note there is no incidental parameters or initial conditions problem in this case as there is no permanent unobserved heterogeneity or serial correlation in the self-rated health or depression (or retirement and morbidity) model. The standard (ordered) probit estimator is consistent and provides asymptotically valid test statistics and standard errors.

on not having been previously diagnosed with heart disease results in nearly identical estimates for parameters in the heart disease equation as the unconditional bivariate probit with constrained lagged effect.

B.3 Simulations

We use the estimated panel VAR model to construct expected remaining lifetime utility for a subset of sixty year old from the HRS. Note that as the HRS began in 1992, age sixty data is not available for the older AHEAD or CODA cohorts, so these are excluded from our welfare analysis. Moreover, the mid- and late-Baby Boomers were only recently added to the survey and do not have the requisite lagged data to estimate welfare. This leaves four cohorts for welfare analyses—the EHRS, LHRS, War Babies, and early Baby Boomers. Our forecasting model requires lagged outcomes implying data is needed from age fifty-eight as part of age sixty "initial" conditions. However, the oldest respondents in the EHRS cohort were already sixty when first interviewed in 1992, so they are dropped from the simulation sample. Effectively, this drops those born in 1931 from the EHRS and leaves the cohort as those born 1932-1936.

The HRS provides respondent level analysis weights for each wave designed to produce representative cohort samples of the non-institutionalized US population. We use base year weights corresponding to when the cohort is approximately age sixty to examine the welfare distribution. Specifically, we use 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 (see appendix A), no individuals were dropped from the simulation due to missing item response. However, individuals were dropped if they were not interviewed at ages 58-59 and 60-61.[8] For example, a member of the EHRS cohort 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 is slightly more female, educated, and white relative to the representative sample. However, the differences are small and generally move in same directions for all cohorts.

Table 3 provides a summary of initial outcome conditions in the simulation sample. By most measures, there was an average decline in age sixty health over cohorts. For example, there were some declines in self-rated health, particularly movements from "excellent" to "very good" health. However, morbidities seem to have shifted even more than self-rated health. For example, prevalence of diabetes increased from 11% to 20% and psychiatric problems increased from 7% to 21%. The shift in CESD depression scale is more mixed across cohorts. The EHRS reported the highest percent of respondents with no depressive systems at age sixty (51%) while the LHRS reported to lowest share (44%). On the other hand, more severe depression at sixty showed a generally increasing trend across cohorts, particularly for Baby Boomers. Average age sixty consumption and retired share increased slightly between the EHRS and LHRS cohorts. However, both declined for War Babies and fell even more for Baby Boomers, presumably due to the timing of the great recession, which hit when Baby Boomers were in their late fifties. Increased longevity (and hence

[8]Due to the timing of the interviews across the calendar year, some respondents were 59 in one wave of the survey and 62 in the next. We treat these age 59 data as age 60 data for our simulations.

savings motive) could also potentially explain some of the decline in flow consumption for later cohorts.

B.3.1 Procedure

Using age sixty data as initial $(t = 0)$ conditions[9], we simulate the remaining life outcomes for each individual (i) as follows:

1. Survival shock u_{i1} is drawn and survival to time $t = 1$ (age 62) is determined according to equation (7). 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 4). This shock vector along with the model outlined in equation (2) 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 using equation (3).

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

5. Given age 62 depression (d_{i1}), self-rated health (s_{i1}) and morbidities (M_{i1}), retirement shock $\varepsilon_{4,i1}$ is drawn to determine age 62 retirement (r_{i1}) using equation (5).

6. Given all other age 62 outcomes $(r_{i1}, d_{i1}, s_{i1}, M_{i1})$, consumption shock $\varepsilon_{5,i1}$ is drawn to determine age 62 consumption (c_{i1}) using equation (6).[10]

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.

A comparison between the average simulated life-cycle profiles and those based on available data is shown by cohort in Figures 4-8. Overall, the simulations match the available aggregated data well suggesting our life-cycle dynamics model provides a reasonable approximation of the underlying data generating processes. The simulations also match the standard deviation of consumption and health utility quite well (Figure 8). Note that by construction, the data and simulations are the same at age 60. However, using only age 60 data and the estimated model parameters, the simulations continue to match the data reasonably well even up to 24 years later (when the EHRS cohort is age 84).

[9]Initial conditions also include unobserved endowments $\hat{\pi}$ estimated from model (6) using the prediction method of De Vos et al. (2015).

[10]ε_5 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, but main results change negligibly with use of a common standard deviation.

B.4 Figures and Tables

Table 1: Estimation sample descriptive statistics by cohort

	AHEAD	CODA	EHRS	LHRS	WB	BB	MBB	LBB
Individuals	7,758	4,233	5,368	5,138	3,628	4,802	5,131	4,650
Observations	37,177	28,535	46,201	46,623	29,037	25,719	18,761	6,038
Age (mean)	81.75	75.23	67.64	62.74	60.47	58.45	55.34	52.70
Hypertension (%)	54.70	57.22	53.42	50.63	49.67	49.78	47.58	44.96
Diabetes (%)	15.46	18.89	19.38	18.16	18.65	20.49	19.80	20.04
Cancer (%)	16.83	17.81	14.02	11.16	10.69	8.52	7.60	6.86
Lung disease (%)	9.45	10.17	9.55	8.51	7.22	6.98	7.58	7.72
Heart disease (%)	35.36	31.02	23.18	19.16	16.86	14.79	12.57	10.74
Stroke (%)	15.30	12.15	7.43	6.06	5.75	5.07	4.39	4.49
Psyche problem (%)	11.85	11.69	11.08	12.87	16.95	19.35	19.41	20.28
Arthritis (%)	55.99	60.17	57.43	52.48	51.82	46.19	39.51	33.06
Difficulty with ADLs (%)	40.50	28.87	24.07	21.73	22.18	21.42	19.50	15.18
Depression (%)								
CESD=0	33.48	41.13	45.39	46.33	46.75	44.26	40.30	36.54
CESD=1	21.25	21.64	20.56	20.36	21.36	21.29	23.14	24.64
CESD=2	14.30	12.55	11.54	11.04	10.94	10.56	11.24	12.56
CESD=3	10.18	8.61	7.53	7.14	6.65	6.68	6.73	7.51
CESD=4	7.46	5.55	5.16	4.85	4.47	4.42	4.77	5.23
CESD=5	5.50	4.18	3.84	3.66	3.32	3.89	3.94	4.29
CESD=6	4.11	3.14	2.91	3.00	2.84	3.40	4.01	3.63
CESD=7	2.43	2.12	2.04	2.27	2.26	3.30	3.44	3.29
CESD=8	1.28	1.09	1.03	1.35	1.40	2.21	2.44	2.31
Self-rated health (%)								
Poor	14.26	10.37	9.29	7.81	6.63	7.76	7.25	7.43
Fair	25.76	21.73	19.37	18.77	16.93	19.64	21.23	22.83
Good	30.86	32.26	31.62	30.88	30.72	30.31	31.27	31.20
Very good	21.35	26.40	28.10	28.96	31.99	30.15	29.44	27.00
Excellent	7.77	9.25	11.63	13.58	13.72	12.15	10.81	11.54
Retired (%)	95.32	90.78	75.68	62.30	56.79	47.18	38.93	34.11
Annual consumption ($1000s, mean)	22.22	24.94	24.84	26.19	26.67	23.63	19.58	17.95
Male (%)	37.59	46.81	45.05	45.29	37.56	42.41	42.52	39.96
Education (%)								
<HS	41.68	32.47	31.19	28.27	21.36	20.10	21.96	22.36
HS	29.62	31.42	32.71	32.85	30.91	24.60	24.97	23.55
Some College	16.34	17.81	18.57	20.51	24.45	28.36	29.27	29.20
College	12.36	18.30	17.53	18.38	23.28	26.94	23.80	24.89
Race (%)								
White	84.95	86.88	80.28	79.92	80.15	67.56	60.15	53.41
Black	12.95	9.69	16.32	15.99	14.89	21.39	26.17	27.28
Other	2.11	3.44	3.40	4.09	4.96	11.05	13.68	19.31

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.

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	3,160	3,091	3,816	3,607	2,697	2,572	3,015	2,737
Male (%)	47.20	46.36	46.82	46.61	47.89	47.92	48.25	47.53
Education (%)								
<HS	29.08	28.88	25.32	25.43	18.73	18.47	14.88	14.94
HS	33.61	33.80	32.04	32.28	30.45	30.27	24.80	24.92
Some College	19.28	19.25	21.56	21.42	24.35	24.45	29.19	28.90
College	18.04	18.08	21.09	20.87	26.46	26.81	31.13	31.24
Race (%)								
White	86.31	86.55	86.15	86.54	85.48	85.95	81.57	81.76
Black	10.38	10.24	10.00	9.97	9.73	9.23	10.81	10.61
Other	3.31	3.20	3.85	3.49	4.79	4.82	7.63	7.63

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.

Table 3: Simulation sample initial conditions by cohort

	EHRS	LHRS	WB	BB
Age (mean)	60	60	60	60
Hypertension (%)	38.00	41.68	47.45	50.48
Diabetes (%)	11.80	12.64	16.26	20.22
Cancer (%)	6.81	8.24	10.72	9.39
Lung disease (%)	7.06	6.74	7.08	7.95
Heart disease (%)	13.72	14.60	15.81	16.04
Stroke (%)	2.88	3.88	5.17	4.52
Psyche problem (%)	7.30	11.73	17.04	20.98
Arthritis (%)	44.61	47.94	51.44	51.81
Difficulty with ADLs (%)	11.75	19.53	22.40	22.40
Depression (%)				
CESD=0	50.98	44.72	49.00	47.92
CESD=1	21.38	21.55	19.45	21.27
CESD=2	9.51	11.45	10.39	8.80
CESD=3	5.92	7.48	6.99	6.45
CESD=4	3.31	4.77	4.44	4.00
CESD=5	3.11	3.65	3.19	3.19
CESD=6	2.55	2.79	2.63	2.79
CESD=7	2.03	2.53	2.28	3.27
CESD=8	1.24	1.05	1.64	2.32
Self-rated health (%)				
Poor	7.31	6.68	6.60	7.26
Fair	15.20	16.71	16.60	17.14
Good	28.32	30.11	31.09	29.39
Very good	31.66	30.80	31.72	34.16
Excellent	17.51	15.70	13.99	12.05
Retired (%)	48.63	50.43	48.06	47.54
Annual consumption ($1000s, mean)	27.59	29.50	28.96	25.86

Notes: Mean and percentage estimates use base year respondent analysis weights. War Babies denoted by WB and Baby Boomers by BB. Consumption is reported in real 2010 dollars. Source: HRS.

Table 4: Morbidity shock covariance matrix (Σ)

	Hyper	Diabetes	Cancer	Lung	Heart	Stroke	Psych	Arthritis	ADLs
Hyper	1.00	0.27	0.05	0.08	0.28	0.29	0.14	0.09	0.10
Diabetes	0.27	1.00	0.06	0.05	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	0.05	0.13
Lung	0.08	0.05	0.13	1.00	0.24	0.11	0.18	0.08	0.18
Heart	0.28	0.10	0.04	0.24	1.00	0.28	0.17	0.09	0.14
Stroke	0.29	0.14	0.06	0.11	0.28	1.00	0.21	0.11	0.39
Psych	0.14	0.08	0.12	0.18	0.17	0.21	1.00	0.16	0.28
Arthritis	0.09	0.04	0.05	0.08	0.09	0.11	0.16	1.00	0.26
ADLs	0.10	0.07	0.13	0.18	0.14	0.39	0.28	0.26	1.00

Table 5: Model estimates for self-rated health, depression, retirement, consumption, and mortality

	Health		Depression		Retirement		Consumption		Mortality	
Variable	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	SE	SE
Hyper	-0.271	0.014	0.015	0.015	0.053	0.034	0.001	0.013	0.101	0.026
Diab	-0.258	0.018	-0.031	0.019	0.113	0.042	-0.002	0.017	0.098	0.032
Cancer	-0.684	0.019	0.065	0.019	0.255	0.046	0.030	0.012	0.656	0.026
Lung	-0.461	0.022	0.106	0.023	0.032	0.064	0.002	0.018	0.412	0.031
Heart	-0.484	0.015	0.044	0.016	0.188	0.040	-0.002	0.018	0.197	0.024
Stroke	-0.482	0.021	0.060	0.023	0.439	0.065	-0.073	0.030	0.240	0.029
Psych	-0.399	0.021	0.527	0.022	0.252	0.054	-0.055	0.019	0.220	0.029
Arthritis	-0.222	0.014	0.090	0.015	0.091	0.032	0.017	0.015	-0.022	0.024
ADL	-0.654	0.013	0.368	0.014	0.376	0.035	-0.063	0.015	0.315	0.019
CESD=1					-0.001	0.019	0.007	0.006	0.018	0.017
CESD=2					0.016	0.026	0.019	0.009	0.089	0.019
CESD=3					0.048	0.033	0.015	0.009	0.121	0.023
CESD=4					0.042	0.041	0.026	0.013	0.137	0.025
CESD=5					0.125	0.044	0.024	0.015	0.125	0.027
CESD=6					0.190	0.051	0.033	0.021	0.136	0.030
CESD=7					0.233	0.060	0.028	0.025	0.036	0.034
CESD=8					0.189	0.076	0.041	0.031	0.071	0.047
Health 2			-0.351	0.013	-0.558	0.041	0.053	0.012	-0.320	0.017
Health 3			-0.646	0.014	-0.712	0.042	0.070	0.014	-0.517	0.019
Health 4			-0.838	0.015	-0.737	0.044	0.085	0.017	-0.624	0.023
Health 5 (best)			-0.937	0.019	-0.733	0.049	0.094	0.022	-0.615	0.032
Lag Hyper	0.149	0.019	-0.051	0.022	0.010	0.046	-0.005	0.013	-0.047	0.026
Lag Diab	0.082	0.025	0.031	0.027	-0.112	0.063	-0.005	0.015	0.072	0.033
Lag Cancer	0.533	0.028	-0.087	0.029	-0.190	0.072	-0.009	0.017	-0.444	0.028
Lag Lung	0.213	0.033	-0.031	0.034	0.121	0.095	-0.011	0.018	-0.115	0.034
Lag Heart	0.281	0.022	-0.027	0.022	-0.148	0.061	0.000	0.013	-0.034	0.025
Lag Stroke	0.349	0.031	-0.015	0.033	-0.340	0.109	-0.004	0.024	-0.047	0.031
Lag Psych	0.257	0.030	-0.242	0.030	-0.063	0.079	0.029	0.019	-0.132	0.031
Lag Arthritis	0.121	0.018	-0.031	0.019	-0.020	0.042	-0.006	0.013	-0.075	0.023
Lag ADL	0.344	0.018	-0.184	0.019	-0.210	0.051	0.008	0.012	-0.113	0.019
Lag CESD=1	-0.072	0.008	0.429	0.008	0.008	0.019	0.006	0.007	-0.033	0.016
Lag CESD=2	-0.124	0.010	0.633	0.011	0.008	0.027	0.017	0.010	-0.016	0.020
Lag CESD=3	-0.134	0.013	0.775	0.012	-0.015	0.034	0.019	0.013	-0.037	0.022
Lag CESD=4	-0.151	0.015	0.890	0.015	-0.014	0.042	0.021	0.015	-0.002	0.027
Lag CESD=5	-0.143	0.017	1.024	0.017	0.007	0.047	0.026	0.016	-0.033	0.029
Lag CESD=6	-0.176	0.019	1.131	0.019	0.018	0.055	0.041	0.021	-0.071	0.031
Lag CESD=7	-0.222	0.023	1.302	0.022	0.093	0.066	0.032	0.019	-0.109	0.038
Lag CESD=8	-0.236	0.029	1.534	0.026	-0.026	0.084	0.028	0.029	-0.138	0.047
Lag Health 2	0.597	0.014	0.045	0.013	-0.078	0.053	0.022	0.012	-0.040	0.018
Lag Health 3	1.080	0.015	0.062	0.015	-0.108	0.054	0.031	0.015	-0.073	0.020
Lag Health 4	1.603	0.016	0.043	0.016	-0.140	0.056	0.043	0.016	-0.105	0.023
Lag Health 5	2.216	0.018	0.047	0.019	-0.202	0.060	0.065	0.018	-0.134	0.031
Time	0.018	0.003	-0.024	0.003	-0.003	0.009	-0.000	0.011	-0.015	0.005
2008+	0.006	0.011	0.006	0.012	-0.058	0.030	-0.046	0.008	0.045	0.021
CODA	0.027	0.016	0.020	0.016	0.063	0.068			-0.008	0.024
Early HRS	0.014	0.022	-0.008	0.022	0.096	0.081			-0.047	0.033
Late HRS	0.001	0.028	-0.006	0.029	0.030	0.095			-0.060	0.043
War Babies	-0.016	0.034	0.004	0.035	0.057	0.111			-0.114	0.054
Boomers	-0.086	0.041	0.040	0.043	0.002	0.132			-0.138	0.066
Mid Boomers	-0.129	0.049	0.066	0.051	-0.083	0.151			-0.179	0.082
Late Boomers	-0.139	0.069	0.107	0.073	-0.074	0.187			-0.077	0.160
Black	-0.044	0.008	0.036	0.009	0.051	0.021			0.060	0.016
Other race	-0.089	0.014	0.048	0.014	-0.053	0.033			-0.075	0.029
Female	0.044	0.007	0.074	0.007	0.126	0.016			-0.225	0.012
HS grad	0.080	0.008	-0.039	0.008	-0.010	0.021			0.042	0.014
Some college	0.112	0.009	-0.070	0.009	-0.045	0.023			0.027	0.017
College grad	0.185	0.010	-0.127	0.011	-0.087	0.026			0.018	0.020
Retired							-0.039	0.013	0.205	0.029
Lag Retired	-0.023	0.013	-0.007	0.013			-0.023	0.014	-0.021	0.025
Lag2 Retired	-0.015	0.012	-0.001	0.013						
Lag Con							0.169	0.004		
Lag2 Con							0.082	0.005		
Constant					-1.146	0.194			-1.820	0.246

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

Table 6: Model estimates for morbidities

	Hypertension		Diabetes		Cancer		Lung disease		Heart disease	
Variable	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Lag Hyper			0.261	0.033	-0.028	0.038	0.082	0.039	0.115	0.033
Lag Diab	0.259	0.049			0.055	0.045	0.040	0.049	0.042	0.042
Lag Cancer	-0.042	0.051	0.023	0.051			0.032	0.057	-0.076	0.049
Lag Lung	0.093	0.058	0.079	0.056	0.085	0.059			0.259	0.050
Lag Heart	0.096	0.043	0.076	0.040	0.010	0.041	0.229	0.039		
Lag Stroke	0.089	0.066	-0.034	0.062	-0.015	0.058	0.010	0.059	0.074	0.053
Lag Psych	0.045	0.054	0.061	0.051	-0.063	0.058	0.077	0.055	0.076	0.048
Lag Arthritis	0.086	0.029	-0.005	0.032	-0.005	0.034	0.134	0.037	0.069	0.029
Lag ADL	0.042	0.032	0.025	0.034	0.013	0.034	0.070	0.035	0.067	0.029
Lag CESD=1	0.002	0.018	-0.010	0.020	0.006	0.020	0.029	0.025	0.001	0.018
Lag CESD=2	0.028	0.024	0.011	0.026	0.013	0.026	0.072	0.030	-0.005	0.024
Lag CESD=3	0.010	0.030	0.015	0.031	-0.011	0.032	0.086	0.034	0.018	0.028
Lag CESD=4	0.030	0.037	-0.039	0.038	0.021	0.037	0.088	0.042	0.026	0.033
Lag CESD=5	0.075	0.040	0.000	0.040	-0.038	0.045	0.051	0.049	0.061	0.039
Lag CESD=6	0.095	0.046	-0.000	0.045	0.038	0.047	0.039	0.051	0.076	0.041
Lag CESD=7	0.100	0.052	-0.011	0.053	0.049	0.054	0.173	0.051	-0.016	0.052
Lag CESD=8	0.009	0.069	0.064	0.066	-0.039	0.073	-0.001	0.071	-0.115	0.071
Lag Health 2	0.023	0.035	0.007	0.032	-0.036	0.033	-0.060	0.032	-0.108	0.029
Lag Health 3	0.023	0.036	-0.012	0.034	-0.060	0.035	-0.123	0.035	-0.162	0.031
Lag Health 4	-0.020	0.038	-0.092	0.037	-0.088	0.038	-0.263	0.039	-0.241	0.034
Lag Health 5	-0.097	0.042	-0.219	0.045	-0.121	0.045	-0.401	0.055	-0.288	0.040
Lag2 Hyper			0.032	0.032	0.058	0.038	-0.089	0.039	0.057	0.032
Lag2 Diab	-0.090	0.052			-0.061	0.048	-0.119	0.052	0.106	0.044
Lag2 Cancer	0.022	0.055	-0.019	0.055			0.062	0.061	0.077	0.052
Lag2 Lung	-0.154	0.064	-0.082	0.061	0.054	0.063			-0.106	0.055
Lag2 Heart	-0.050	0.046	0.013	0.042	0.025	0.043	-0.098	0.041		
Lag2 Stroke	-0.036	0.074	0.057	0.067	0.013	0.064	0.014	0.065	0.062	0.058
Lag2 Psych	-0.026	0.057	-0.065	0.054	0.064	0.061	0.050	0.058	-0.020	0.050
Lag2 Arthre	-0.043	0.029	-0.009	0.032	0.048	0.034	-0.031	0.036	0.032	0.029
Lag2 ADL	-0.050	0.035	0.035	0.036	-0.018	0.036	-0.010	0.036	0.010	0.031
Lag2 CESD=1	0.006	0.019	0.027	0.021	0.013	0.020	0.046	0.024	0.012	0.018
Lag2 CESD=2	-0.030	0.025	0.049	0.026	-0.005	0.026	0.029	0.029	0.040	0.023
Lag2 CESD=3	0.027	0.029	0.058	0.033	0.065	0.031	0.077	0.034	-0.055	0.029
Lag2 CESD=4	0.034	0.036	0.060	0.038	0.018	0.039	0.022	0.041	-0.015	0.035
Lag2 CESD=5	-0.040	0.044	0.021	0.044	0.019	0.045	-0.024	0.050	0.040	0.038
Lag2 CESD=6	0.028	0.048	-0.014	0.048	-0.002	0.051	0.048	0.050	-0.004	0.043
Lag2 CESD=7	0.046	0.056	0.034	0.052	0.100	0.054	0.019	0.057	0.085	0.048
Lag2 CESD=8	0.043	0.070	-0.039	0.072	-0.179	0.088	0.133	0.067	-0.005	0.066
Lag2 Health 2	-0.018	0.037	-0.066	0.033	-0.053	0.035	-0.082	0.034	0.003	0.032
Lag2 Health 3	-0.015	0.038	-0.060	0.035	-0.009	0.037	-0.115	0.037	-0.009	0.033
Lag2 Health 4	-0.031	0.039	-0.107	0.038	0.002	0.039	-0.159	0.040	-0.034	0.036
Lag2 Health 5	-0.060	0.043	-0.138	0.044	0.009	0.045	-0.250	0.052	-0.081	0.041
Time	0.040	0.007	0.027	0.008	0.004	0.008	0.013	0.009	-0.005	0.007
2008+	-0.057	0.027	-0.064	0.029	0.016	0.029	-0.008	0.034	-0.049	0.026
CODA	-0.031	0.038	-0.022	0.042	-0.020	0.039	0.002	0.044	-0.014	0.035
Early HRS	-0.086	0.052	-0.043	0.057	-0.078	0.053	-0.054	0.061	0.021	0.048
Late HRS	-0.080	0.066	-0.042	0.072	-0.100	0.069	-0.005	0.078	0.040	0.061
War Babies	-0.091	0.081	0.007	0.089	-0.071	0.085	-0.012	0.098	0.069	0.076
Boomers	-0.170	0.099	0.033	0.108	-0.127	0.105	-0.036	0.119	0.105	0.092
Mid Boomers	-0.305	0.117	0.053	0.127	-0.097	0.125	0.022	0.142	0.133	0.110
Late Boomers	-0.327	0.156	0.211	0.163	-0.158	0.196	-0.009	0.210	0.116	0.165
Black	0.188	0.021	0.079	0.021	-0.035	0.022	-0.145	0.025	-0.133	0.020
Other race	0.064	0.030	0.210	0.031	-0.175	0.040	-0.090	0.041	-0.103	0.033
Female	0.016	0.015	-0.106	0.017	-0.202	0.017	-0.051	0.020	-0.174	0.015
HS grad	-0.039	0.018	-0.076	0.019	0.007	0.020	-0.079	0.022	0.026	0.018
Some college	-0.074	0.021	-0.074	0.022	0.048	0.023	-0.073	0.026	0.050	0.021
College grad	-0.117	0.024	-0.137	0.026	0.050	0.026	-0.183	0.032	-0.020	0.024
Lag Retired	-0.015	0.029	0.024	0.030	0.036	0.032	0.070	0.038	0.016	0.029
Lag2 Retired	-0.004	0.028	-0.019	0.030	-0.014	0.031	-0.002	0.036	-0.016	0.029
Constant	-1.582	0.087	-2.055	0.093	-1.951	0.094	-2.108	0.108	-1.752	0.084

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

Table 7: Model estimates for morbidities (continued)

	Stroke		Psych		Arthritis		ADLs	
Variable	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Lag Hyper	0.099	0.040	0.129	0.037	0.072	0.032	0.040	0.030
Lag Diab	0.035	0.052	0.015	0.050	0.055	0.044	0.083	0.039
Lag Cancer	-0.030	0.058	-0.043	0.059	0.065	0.050	0.024	0.043
Lag Lung	0.015	0.062	0.089	0.062	0.157	0.064	0.160	0.048
Lag Heart	0.184	0.039	0.079	0.041	0.090	0.041	0.076	0.033
Lag Stroke			0.249	0.051	-0.027	0.061	0.370	0.046
Lag Psych	0.124	0.053			0.254	0.053	0.274	0.043
Lag Arthritis	-0.005	0.036	0.109	0.035			0.206	0.025
Lag ADL	0.164	0.032	0.149	0.032	0.152	0.036		
Lag CESD=1	0.022	0.023	0.081	0.024	0.050	0.018	0.095	0.017
Lag CESD=2	0.033	0.028	0.180	0.029	0.042	0.024	0.167	0.021
Lag CESD=3	0.062	0.034	0.226	0.034	0.010	0.033	0.218	0.025
Lag CESD=4	0.062	0.039	0.352	0.038	0.083	0.037	0.230	0.031
Lag CESD=5	0.171	0.043	0.362	0.042	0.055	0.043	0.235	0.036
Lag CESD=6	0.135	0.048	0.341	0.050	0.071	0.049	0.214	0.043
Lag CESD=7	0.138	0.054	0.442	0.054	0.035	0.059	0.353	0.047
Lag CESD=8	0.022	0.072	0.537	0.070	0.024	0.077	0.353	0.062
Lag Health 2	-0.114	0.031	-0.147	0.031	-0.069	0.037	-0.182	0.030
Lag Health 3	-0.187	0.034	-0.185	0.033	-0.092	0.038	-0.388	0.031
Lag Health 4	-0.217	0.039	-0.254	0.038	-0.131	0.040	-0.537	0.033
Lag Health 5	-0.336	0.050	-0.330	0.050	-0.226	0.044	-0.604	0.040
Lag2 Hyper	0.042	0.039	-0.072	0.037	0.028	0.033	-0.015	0.030
Lag2 Diab	0.091	0.054	0.014	0.053	-0.046	0.047	0.024	0.041
Lag2 Cancer	0.006	0.062	0.071	0.063	-0.018	0.054	-0.010	0.046
Lag2 Lung	0.045	0.067	0.028	0.067	-0.066	0.071	-0.018	0.053
Lag2 Heart	-0.029	0.041	-0.064	0.043	-0.019	0.044	-0.075	0.035
Lag2 Stroke			-0.152	0.058	0.018	0.068	-0.173	0.052
Lag2 Psych	-0.031	0.056			-0.116	0.057	-0.136	0.046
Lag2 Arthre	-0.014	0.035	-0.025	0.034			0.044	0.025
Lag2 ADL	-0.089	0.034	-0.071	0.034	-0.053	0.041		
Lag2 CESD=1	-0.011	0.023	0.059	0.023	0.022	0.018	0.091	0.016
Lag2 CESD=2	0.014	0.028	0.071	0.031	0.031	0.026	0.101	0.021
Lag2 CESD=3	-0.023	0.035	0.183	0.034	0.041	0.032	0.096	0.027
Lag2 CESD=4	-0.036	0.045	0.212	0.038	0.028	0.038	0.152	0.032
Lag2 CESD=5	0.015	0.045	0.137	0.048	0.001	0.047	0.168	0.037
Lag2 CESD=6	0.015	0.051	0.205	0.051	0.001	0.054	0.176	0.043
Lag2 CESD=7	-0.044	0.058	0.250	0.055	-0.033	0.063	0.162	0.052
Lag2 CESD=8	0.044	0.072	0.348	0.076	0.110	0.077	0.219	0.067
Lag2 Health 2	-0.052	0.034	-0.024	0.033	0.037	0.040	-0.136	0.033
Lag2 Health 3	-0.053	0.037	-0.028	0.036	0.056	0.041	-0.229	0.033
Lag2 Health 4	-0.031	0.040	-0.092	0.040	0.030	0.043	-0.321	0.035
Lag2 Health 5	-0.071	0.049	-0.135	0.049	-0.035	0.046	-0.385	0.041
Time	-0.025	0.008	0.010	0.008	-0.032	0.007	-0.048	0.006
2008+	0.018	0.032	-0.104	0.033	0.021	0.028	0.040	0.025
CODA	0.012	0.038	0.067	0.042	-0.104	0.038	0.089	0.031
Early HRS	0.003	0.053	0.066	0.058	-0.108	0.053	0.134	0.044
Late HRS	0.015	0.069	0.108	0.074	-0.017	0.066	0.137	0.057
War Babies	0.099	0.086	0.227	0.091	0.103	0.081	0.167	0.070
Boomers	0.086	0.105	0.309	0.111	0.135	0.099	0.250	0.086
Mid Boomers	0.152	0.128	0.300	0.131	0.159	0.117	0.322	0.101
Late Boomers	0.549	0.195	0.040	0.195	0.209	0.153	0.309	0.148
Black	0.051	0.023	-0.207	0.025	-0.002	0.020	0.084	0.018
Other race	-0.128	0.045	-0.049	0.038	-0.047	0.031	0.045	0.031
Female	-0.071	0.019	0.104	0.019	0.161	0.015	-0.029	0.014
HS grad	0.044	0.021	-0.047	0.021	-0.027	0.019	-0.078	0.016
Some college	0.059	0.025	0.030	0.025	0.009	0.021	-0.025	0.019
College grad	0.053	0.030	0.004	0.029	-0.024	0.024	-0.070	0.022
Lag Retired	0.068	0.040	0.052	0.037	0.003	0.028	0.153	0.026
Lag2 Retired	-0.003	0.037	-0.009	0.036	-0.032	0.028	-0.071	0.025
Constant	-2.575	0.112	-2.234	0.099	-1.342	0.088	-1.239	0.078

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

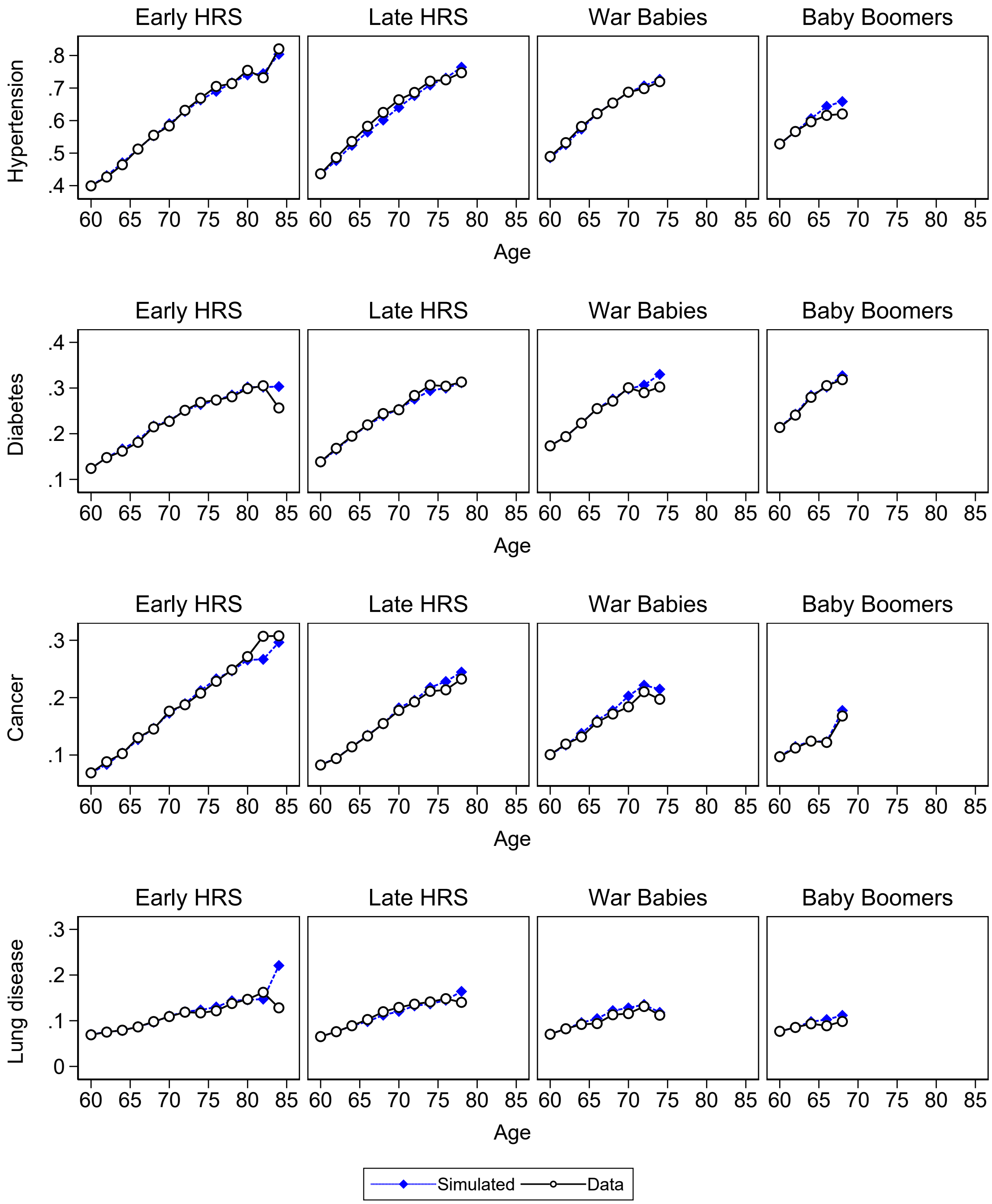

Figure 4: Mean of life-cycle morbidity profiles by cohort

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).

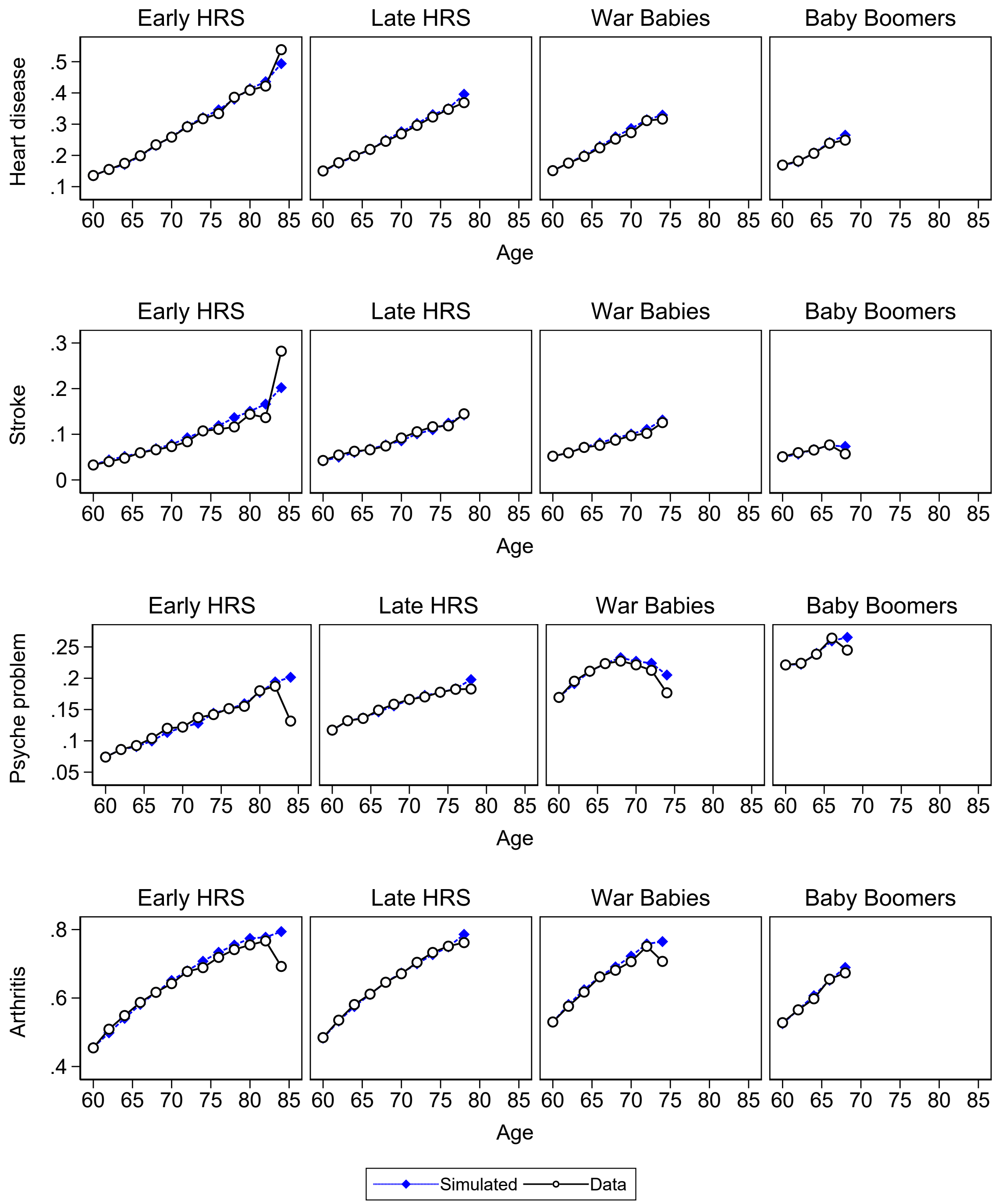

Figure 5: Mean of life-cycle morbidity profiles by cohort

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).

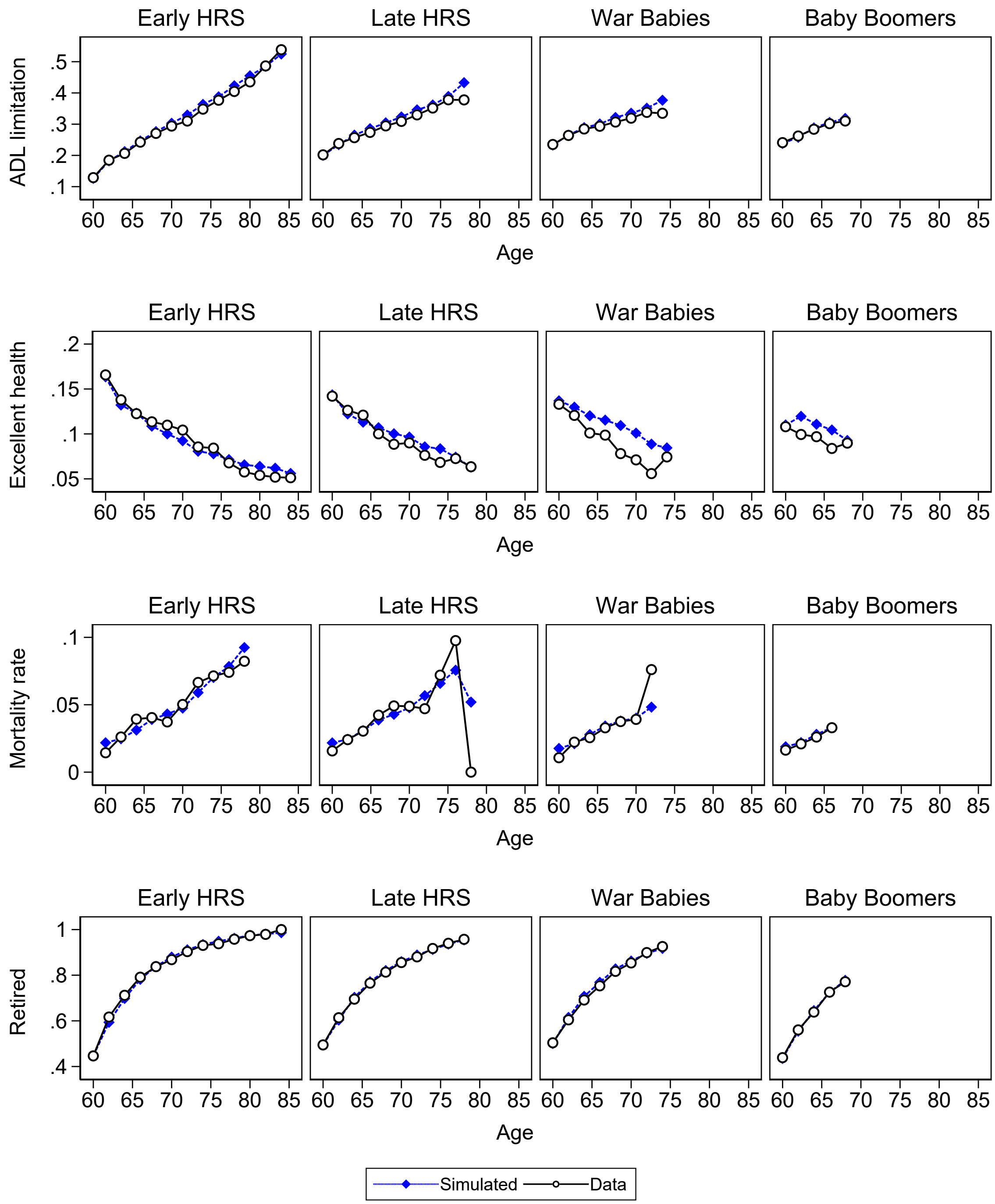

Figure 6: Mean of life-cycle health, mortality, and retirement profiles by cohort

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).

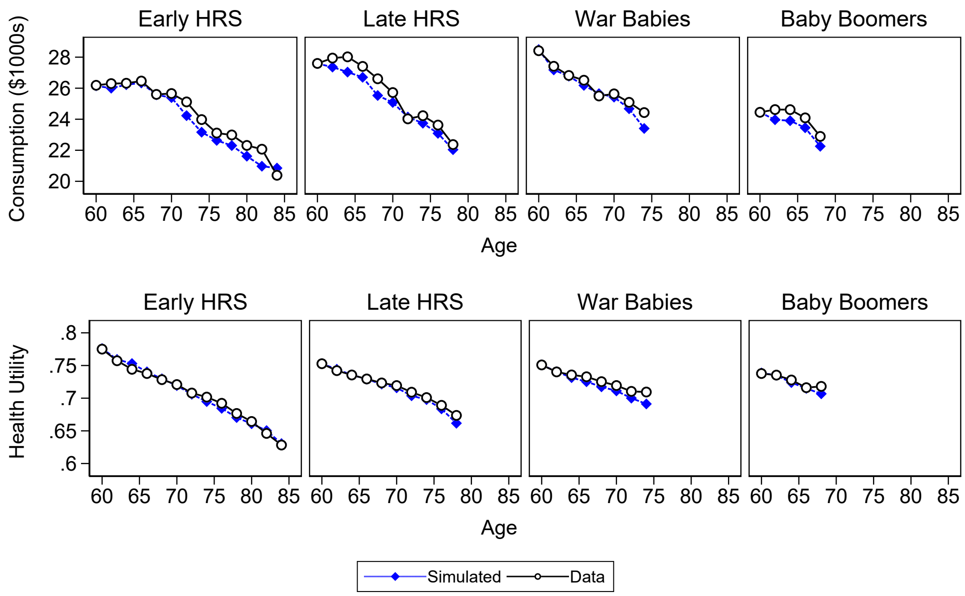

Figure 7: Mean of life-cycle consumption and health utility profiles by cohort

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).

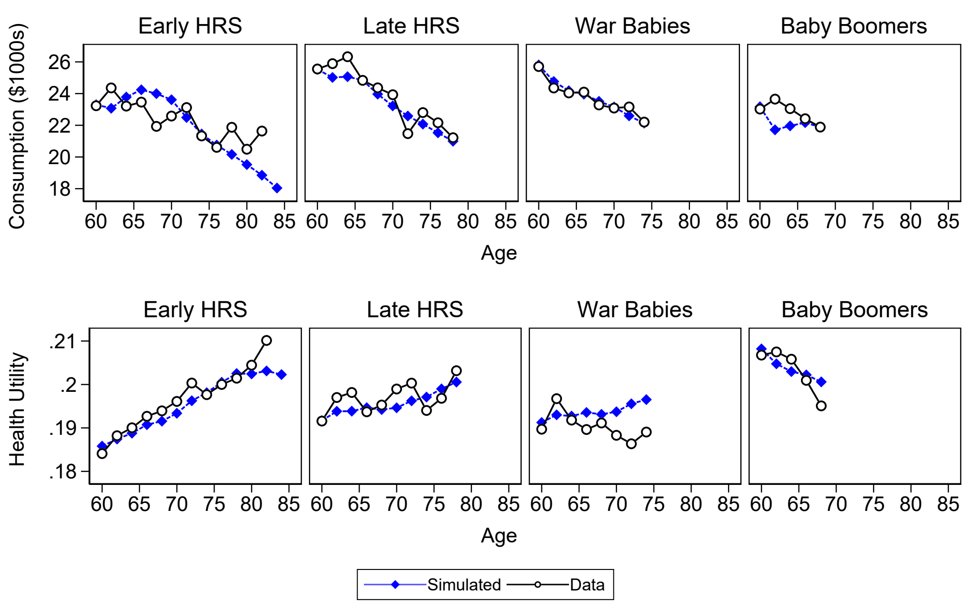

Figure 8: Standard deviation of consumption and health utility life-cycle profiles by cohort

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).

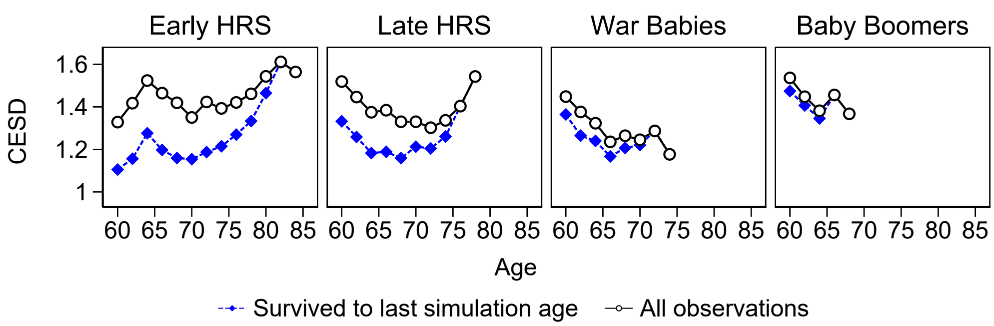

Figure 9: Mean of life-cycle CESD profiles by cohort

Notes: "All observations" plots mean of all available data (inclusive of imputed missing values) in HRS by two-year age interval and cohort. "Survived to last simulation age" plots mean data for all individuals that survived to the last simulation age.

C Welfare decomposition

Welfare condition (8) may be rewritten:

$$log\left(1-\lambda_{ij}\right)=\frac{U_{ij}\left(1\right)-U_{mj}\left(1\right)}{E\left[\sum_{a=j}^{J}\psi_{ma}\beta^{a-j}\phi\left(h_{ma}\right)\right]}.$$

Let u_{ia} denote flow utility unadjusted for health at age a given outcome bundles i: $u_{ia}=\bar{u}+log\left(c_{ia}\right)+\nu\left(l_{ia}\right)$. Moreover, denote the expected value conditional on survival with subscript ψ: $E_{\psi}\left[u_{ia}\right]=E\left[u_{ia}\mid\psi_{ia}=1\right]$. Note that the welfare condition under our benchmark preference specification is then given as:

$$\begin{aligned}
log\left(1-\lambda_{ij}\right) &= \tilde{\psi}\left(U_{ij}-E\left[\sum_{a=j}^{J}\psi_{ma}\beta^{a-j}\phi\left(h_{ma}\right)\left[\bar{u}+log\left(c_{ma}\right)+\nu\left(l_{ma}\right)\right]\right]\right)\\
&= \tilde{\psi}\left(E\left[\sum_{a=j}^{J}\psi_{ia}\beta^{a-j}\phi(h_{ia})u_{ia}\right]-E\left[\sum_{a=j}^{J}\psi_{ma}\beta^{a-j}\phi\left(h_{ma}\right)\left[\bar{u}+log\left(c_{ma}\right)+\nu\left(l_{ma}\right)\right]\right]\right)\\
&= \tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left(E\left[\psi_{ia}\phi(h_{ia})u_{ia}\right]-E\left[\psi_{ma}\phi\left(h_{ma}\right)\left[\bar{u}+log\left(c_{ma}\right)+\nu\left(l_{ma}\right)\right]\right]\right)
\end{aligned}$$

where $\tilde{\psi}$ is the reciprocal of the reference discounted quality-adjusted life expectancy (QALE):

$$\tilde{\psi}=\frac{1}{E\left[\sum_{a=j}^{J}\psi_{ma}\beta^{a-j}\phi\left(h_{ma}\right)\right]}.$$

Also note that $E\left[\psi_{ia}u_{ia}\right]=E\left[\psi_{ia}\right]E_{\psi}\left[u_{ia}\right]$ from the definition of conditional probability where $E_{\psi}\left[u_{ia}\right]$ denotes the expected flow utility conditional on survival. Then adding and subtracting the term:

$$\begin{aligned}
\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\Bigg(& E\left[\psi_{ia}\phi\left(h_{ia}\right)\right]E_{\psi}\left[u_{ia}\right]+E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]\left(E_{\psi}\left[u_{ia}\right]-E_{\psi}\left[\bar{u}+log\left(c_{ma}\right)+\nu\left(l_{ma}\right)\right]\right)\\
&+\left(E\left[\psi_{ia}\right]-E\left[\psi_{ma}\right]\right)E_{\psi}\left[\phi\left(h_{ma}\right)\right]E_{\psi}\left[u_{ia}\right]\\
&+\left(E_{\psi}\left[\phi\left(h_{ia}\right)\right]-E_{\psi}\left[\phi\left(h_{ma}\right)\right]\right)E\left[\psi_{ia}\right]E_{\psi}\left[u_{ia}\right]\Bigg).
\end{aligned}$$

from the right hand side of the above welfare condition gives:

$$
\begin{aligned}
log\left(1-\lambda_{ij}\right) = &\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left(E\left[\psi_{ia}\phi(h_{ia})u_{ia}\right]-E\left[\psi_{ma}\phi\left(h_{ma}\right)\left[\bar{u}+log\left(c_{ma}\right)+\nu\left(l_{ma}\right)\right]\right]\right)\\
&+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\Big(E\left[\psi_{ia}\phi\left(h_{ia}\right)\right]E_{\psi}\left[u_{ia}\right]+E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]\left(E_{\psi}\left[u_{ia}\right]-E_{\psi}\left[\bar{u}+log\left(c_{ma}\right)+\nu\left(l_{ma}\right)\right]\right)\Big)\\
&+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\Big(\left(E\left[\psi_{ia}\right]-E\left[\psi_{ma}\right]\right)E_{\psi}\left[\phi\left(h_{ma}\right)\right]E_{\psi}\left[u_{ia}\right]\Big)\\
&+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\Big(\left(E_{\psi}\left[\phi\left(h_{ia}\right)\right]-E_{\psi}\left[\phi\left(h_{ma}\right)\right]\right)E\left[\psi_{ia}\right]E_{\psi}\left[u_{ia}\right]\Big)\\
&-\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\Big(E\left[\psi_{ia}\phi\left(h_{ia}\right)\right]E_{\psi}\left[u_{ia}\right]+E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]\left(E_{\psi}\left[u_{ia}\right]-E_{\psi}\left[\bar{u}+log\left(c_{ma}\right)+\nu\left(l_{ma}\right)\right]\right)\Big)\\
&-\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\Big(\left(E\left[\psi_{ia}\right]-E\left[\psi_{ma}\right]\right)E_{\psi}\left[\phi\left(h_{ma}\right)\right]E_{\psi}\left[u_{ia}\right]\Big)\\
&-\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\Big(\left(E_{\psi}\left[\phi\left(h_{ia}\right)\right]-E_{\psi}\left[\phi\left(h_{ma}\right)\right]\right)E\left[\psi_{ia}\right]E_{\psi}\left[u_{ia}\right]\Big)
\end{aligned}
$$

Rearranging the terms of the above equation and using the definition of $E\left[\psi_{ia}u_{ia}\right]$ yields the following additive decomposition of welfare:

$$
\begin{aligned}
log\left(1-\lambda_{ij}\right) = &+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left[\left(E_{\psi}\left[\phi\left(h_{ia}\right)\right]-E_{\psi}\left[\phi\left(h_{ma}\right)\right]\right)E\left[\psi_{ia}\right]E_{\psi}\left[u_{ia}\right]+\Phi\right]. && \text{Health} \quad (1)\\
&+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left(E\left[\psi_{ia}\right]-E\left[\psi_{ma}\right]\right)E_{\psi}\left[\phi\left(h_{ma}\right)\right]E_{\psi}\left[u_{ia}\right] && \text{Mortality} \quad (2)\\
&+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]\left(E_{\psi}\left[\nu\left(l_{ia}\right)\right]-E_{\psi}\left[\nu\left(l_{ma}\right)\right]\right) && \text{Leisure} \quad (3)\\
&\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left[E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]\left(E_{\psi}\left[log\left(c_{ia}\right)\right]-E_{\psi}\left[log\left(c_{ma}\right)\right]\right)\right] && \text{Consumption} \quad (4)
\end{aligned}
$$

where

$$
\begin{aligned}
\Phi = &\left(E\left[\psi_{ia}\phi\left(h_{ia}\right)u_{ia}\right]-E\left[\psi_{ia}\phi\left(h_{ia}\right)\right]E_{\psi}\left[u_{ia}\right]\right)\\
&-\left(E\left[\psi_{ma}\phi\left(h_{ma}\right)\nu\left(l_{ma}\right)\right]-E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]E_{\psi}\left[\nu\left(l_{ma}\right)\right]\right).
\end{aligned}
$$

The first term in (1) is the expected utility gain from eliminating depression due only to gains in health utility—holding life expectancy, leisure, and consumption at their baseline levels. The Φ term is an adjustment for uncertainty over the life-cycle (the quantitative value of this term is generally quite small). Combined, these provide an individual's consumption-equivalent welfare before adjusting for expected differences in life expectancy, leisure, or consumption. The correction term (2) is the difference in life expectancy weighted by how much a life year is worth—the expected flow utility from outcome bundles of individual i in the baseline. The term (3) is the welfare adjustment for leisure—the expected utility difference in leisure weighted by the depression-free quality-adjusted life expectancy. Finally, term (4) corrects for expected consumption differences from eliminating depression over remaining life.

D Bootstrap standard errors

In order to gain a sense of how uncertainty in the underlying simulation model translates into uncertainty in our main welfare results, we estimate bootstrap standard errors and confidence intervals. This is computationally intensive so we pooled estimates across our imputed data sets. Specifically, for each of the $m = 12$ imputed data sets, we drew 30 bootstrap samples yielding a total of $m \times 30 = 360$ data sets. We then estimated our main welfare numbers in each data set. Finally, we pooled estimates across all 360 to estimate standard errors (see Schomaker and Heumann (2018) for validation of this approach with multiple imputation). Table 8 provides estimated bootstrap standard errors for the depression only and full model results. Overall, standard errors are quite small relative to point estimates and all major conclusions from our main analyses hold.

Table 8: Bootstrap estimated mean costs of depression after age sixty by birth cohort

	Depression only				Full model			
	EHRS	LHRS	WB	BB	EHRS	LHRS	WB	BB
Expected loss								
QALYs	0.853	0.826	0.793	0.816	2.059	1.972	1.884	1.924
	(0.016)	(0.019)	(0.025)	(0.035)	(0.093)	(0.100)	(0.100)	(0.115)
Labor supply (yrs)					0.093	0.097	0.094	0.111
					(0.031)	(0.032)	(0.031)	(0.036)
Consumption (annual)					-0.138	-0.144	-0.133	-0.125
					(0.086)	(0.086)	(0.080)	(0.076)
CV (λ)	0.084	0.083	0.078	0.076	0.148	0.144	0.134	0.129
	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.007)	(0.007)	(0.007)
$\lambda \times$ELC	47.164	48.099	45.779	42.953	91.501	92.989	87.962	82.352
	(1.562)	(1.330)	(1.972)	(2.483)	(5.047)	(5.395)	(5.638)	(6.365)
CV Gini	0.337	0.358	0.380	0.416	0.281	0.292	0.315	0.343
	(0.006)	(0.006)	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)

Notes: Bootstrap standard errors in parentheses. Estimates use base year respondent analysis weights. ELC denotes expected lifetime consumption. Consumption in $1000s.

Figure 10 further provides bootstrap standard errors for the outcome profiles in Figure 4 of the main text. Given the computational costs of bootstrapping we show standard errors only for overall health utility and not for each morbidity separately. Again standard errors are small relative to the point estimates provided in Figure 4 of the paper.

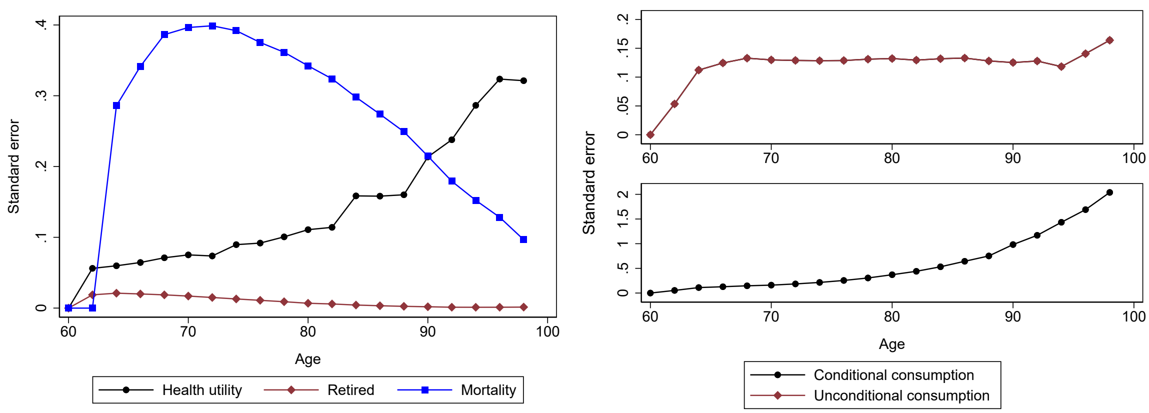

Figure 10: Standard errors of expected cost of depression by age

Notes: Results plot bootstrap standard errors for percentage difference in expected outcomes with the exogenous elimination of all prevalence of depression after age sixty. Sample includes all individuals in the simulation sample. Expected outcomes in first panel are conditional on survival.

E Robustness results

Here we present and discuss some additional robustness results (see Table 9).

Table 9: Additional robustness results

	Depression only				Full model			
	EHRS	LHRS	WB	BB	EHRS	LHRS	WB	BB
Benchmark	0.084	0.083	0.077	0.075	0.148	0.144	0.134	0.128
β = 0.90	0.078	0.079	0.073	0.072	0.121	0.119	0.110	0.105
ε = 0.5	0.085	0.084	0.079	0.077	0.151	0.147	0.137	0.131
ε = 2	0.082	0.081	0.075	0.073	0.144	0.140	0.130	0.124
θ = 16	0.082	0.081	0.075	0.074	0.145	0.141	0.131	0.125
Health utility weights	0.091	0.090	0.083	0.081	0.153	0.148	0.137	0.131
NH consumption	0.098	0.096	0.090	0.089	0.152	0.148	0.140	0.136
No imputed CESD	0.084	0.083	0.078	0.076	0.148	0.144	0.135	0.128
No imputed data	–	0.077	0.063	0.060	–	0.102	0.084	0.076
Depression impact health	0.084	0.083	0.077	0.075	0.189	0.184	0.171	0.162
Full-time job	0.084	0.084	0.078	0.076	0.150	0.146	0.136	0.130

Notes: Mean CV (λ) reported. Estimates use base year respondent analysis weights. War Babies denoted by WB and Baby Boomers by BB.

E.1 Preference parameters

Rows 2-5 in Table 9 indicate sensitivity of our results to preference parameters β, ε and θ. With a lower time discount rate $\beta = 0.90$, the estimated mean welfare cost of late-life depression in the EHRS falls slightly to 7-12% of annual consumption. Raising or lowering the Frisch elasticity of labor supply ε or increasing disutility weight on labor supply θ have very minimal impacts on our welfare estimates as labor supply plays a relatively small role overall. In all cases, there are similar changes in welfare estimates for later cohorts and we continue to see a small decline in mean welfare costs across cohorts.

E.2 Health utility weights

In our calibration of health utility weights we assumed that the HUI3 measures relative utility across health states holding consumption and leisure fixed. While this approach is consistent with the interview instructions of the survey, there is some uncertainty around if respondents were fully capable of conceptualizing changing health states without changes in other aspects of life (Feeny et al., 2018). For example, if respondents considered changes in consumption and leisure in addition to health, the appropriate representation of the HUI3 instrument would be:

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

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

$$\omega h=HUI3\frac{\bar{u}+log\left(c_{best}\right)+\nu\left(l_{best}\right)}{\bar{u}+log\left(c\right)+\nu\left(l\right)}. \tag{5}$$

Generally, 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. However, as we have already developed an independent forecasting model, we can predict the expected value for c_{best} and l_{best} for each individual in the sample. With these predictions in hand, we estimated the right hand side of (5) for each HUI3 respondent. We then regressed this value on CESD scale, self-rated health, and all morbidity indicators to obtain alternate utility weights ω (see results in Table 10). The sixth row in Table 9 shows that using these alternate utility weights very slightly increases the estimated mean welfare cost of late-life depression in all cohorts.

Table 10: Estimated alternate health utility weights (ω)

Measure	Weight	SE
Depression		
CESD=1	-0.014	0.023
CESD=2	-0.107	0.028
CESD=3	-0.095	0.034
CESD=4	-0.117	0.040
CESD=5	-0.082	0.045
CESD=6	-0.176	0.051
CESD=7	-0.285	0.066
CESD=8	-0.236	0.071
Hypertension	0.005	0.018
Diabetes	0.006	0.025
Cancer	0.021	0.024
Lung disease	-0.018	0.029
Heart disease	-0.031	0.020
Stroke	-0.038	0.031
Psych problem	-0.026	0.028
Arthritis	-0.041	0.018
Diff with ADL	-0.100	0.022
Self-rated health		
Fair	0.199	0.035
Good	0.251	0.037
Very good	0.324	0.039
Excellent	0.318	0.044
Constant	0.524	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.

E.3 Nursing home consumption

For our measure of individual consumption we use household consumption from CAMS (minus health spending) divided by the number of household members. However, the number of household members excludes those residing in nursing homes. This means we are implicitly imputing average household consumption for members residing in nursing homes. For example, assume a couple has one member in a nursing home and one residing at home. Assume the member at home reported consumption of $20,000 on the CAMS survey. In this case, both members would be given $20,000 of consumption in our benchmark model. We believe this to be a reasonable imputation as much of the reported consumption is likely to be for the individual residing at home while the other member receives in-kind consumption from the nursing home (which could vary with nursing home quality). Also, note that if both members of a couple (or single person) are in a nursing home, the household does not receive a CAMS survey and consumption is imputed through multiple imputation.

Here we try to get a sense of how sensitive results are to our assumptions about nursing home consumption. Specifically, instead of assuming average household consumption or using multiple imputation to assign consumption for those in nursing homes, we simply set nursing home consumption to \$6,000. We choose this amount because it is roughly equivalent to average annual Supplementary Security Income (SSI) reported in our sample. Many nursing home residents rely on Medicaid which is often tightly connected to SSI. The seventh row in Table 9 provides results from this robustness exercise. With the generally lower nursing home consumption of \$6,000, the estimated welfare costs of depression increase slightly. For example, the fully-adjusted measure for the EHRS cohort increased from a benchmark value of 0.148 up to 0.152. This suggests a likely positive correlation between nursing home residence and depression. However, this correlation is not so strong that our overall results are likely to be highly biased by choice of consumption imputation for nursing home residents.

E.4 Non-imputed data

We also checked the sensitivity of results to the use of imputed data. As depression is the focus of our analyses, we begin by estimating results after dropping the approximately 12% of observations with missing CESD score instead of using multiple imputation. Row eight of Table 9 shows that results change very little when dropping missing CESD scores. The following row provides results when dropping all missing data instead of imputing. Consumption is by far the variable with the most missing cases. Recall that consumption data is only available for about 20% of the sample after 2001. As the EHRS cohort was already over age sixty by this time, simulations cannot be run for the cohort as they are all missing initial age sixty consumption. Moreover, only about 15% of the simulation sample remains for the younger cohorts and these observations are unlikely to be representative of the larger older adult population. One of the main benefits of multiple imputation is that the sample remains representative. Moreover, our imputation procedure utilizes a lot of related information (e.g., income and wealth) that is thrown out when dropping missing consumption. When excluding all cases with missing data, the depression cost estimates are somewhat lower. For example, the lower bound falls from 0.083 to 0.077 for the LHRS cohort. The decline in the upper bound is somewhat more substantial—for example, falling from 0.144 to 0.102 in LHRS cohort. Nonetheless, there are still substantial estimated costs that decline somewhat over birth cohorts as in the benchmark.

E.5 Depression impacting health

In our benchmark estimation we assumed self-rated health impacted depression but depression did not contemporaneously impact self-rated health. This assumption was made for block identification of the VAR system. We argued this also likely yields conservative estimates of the welfare costs of depression. Here we test this argument by instead allowing depression to impact contemporaneous self-rated health while assuming self-rated health does not contemporaneously impact depression. Table 9 provides the results of this simulation. The lower bound estimates change very little while the upper bounds increase somewhat as expected. For example, the upper bound estimate for the EHRS cohort increased from a benchmark value of 0.148 up to 0.189. These results support the argument of conservative cost estimates in our benchmark results.

E.6 Labor hours

In our benchmark we classified retirement as working zero hours. Here we check the robustness of results to defining retirement as not working full-time. In practice, retirement can take many levels in-between, but comparing the full-time definition to our zero hours benchmark should give a sense of how sensitive results might be to intermediate possibilities like partial retirement. We follow the RAND data file and define full-time employment as working at least 1,260 hours annually (35+ hours a week for 36+ weeks a year). We combine data on weekly hours worked and weeks worked per year to estimate annual hours worked. The last row of Table 9 shows that results are largely insensitive to this change in retirement definition. This is perhaps unsurprising given the limited role found for retirement in our benchmark results.

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