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The Effect of US COVID-19 Excess Mortality on Social Security Outlays
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ABSTRACT

The COVID-19 pandemic has resulted in significant excess mortality among the US population, impacting the future outlays of the US Social Security Administration (SSA) Old Age, Survivors, and Disability Insurance (OASDI) program. This study aimed to estimate the net effects of pandemic-induced excess deaths on OASDI liabilities, utilizing dynamic microsimulation models, and examined how these effects vary across different socioeconomic and racial-ethnic groups. Data on excess deaths were obtained from the CDC and processed to account for seasonal variations and demographic disparities. The simulation incorporated demographic and health status variables to project OASDI retirement and disability benefits, and survivors' benefits for spouses and children, for respondents with highest COVID mortality risk. The pandemic resulted in approximately 1.7 million excess deaths among individuals aged 25 and older between 2020 and 2023. These premature deaths reduced future retirement payments, which increased the Social Security fund by $294 billion. However, this gain was offset by reductions in future payroll tax flows ($58 billion) and increased payments to surviving spouses and children ($32 billion), resulting in a net impact of $205 billion. Non-Hispanic Black and Hispanic decedents left behind more underage children per capita, yet payments to their surviving family members were lower compared to non-Hispanic White decedents, across all educational levels. Excess mortality during the COVID-19 pandemic has complex implications for the OASDI program. While there is an estimated net positive financial impact due to reduced future retirement benefits, this effect is mitigated by decreased payroll tax contributions and increased survivors' benefits. The differential impact by race and ethnicity highlights existing inequalities and underscores the importance of considering demographic disparities in future projections of Social Security liabilities. These findings provide critical insights for informing SSA trust fund projections and policy decisions.

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Introduction

The COVID-19 pandemic has resulted in over 1.7 million excess deaths among the US population as of 2023. The effects of these deaths on the expected future outlays of the US Old-Age, Survivors, Disability Insurance (OASDI) program remains uncertain. The OASDI program, commonly referred to as "Social Security," provides retirement benefits, survivors' benefits, and disability insurance benefits. While excess mortality directly reduces spending on Social Security annuity benefits, the pandemic also resulted in earlier and more widespread survivors' benefits for spouses and children left behind by pandemic decedents. The budgetary implications of these deaths ranks among the larger set of questions surrounding the long-term effects of the COVID-19 pandemic on OASDI liabilities, including the ultimate impacts of long COVID and of the pandemic-induced recession.

Estimating the budgetary effects of COVID-19 solely on the basis of excess deaths and average benefits may misrepresent the net effect on OASDI liabilities if pandemic decedents differ from the average beneficiary. For example, our previous work estimated that 62% of pandemic decedents would have experienced below-average life expectancies for their age-sex-race/ethnicity subgroup, which limits the expected reduction in future outlays, all else equal (1). At the same time, we also showed non-Hispanic Black and Hispanic males lost nearly three times the number of life years as non-Hispanic white males for people under 65 and more than twice the number of life-years among people over age 65. This finding highlights the potential for significant racial disparities in expected future OASDI outlays.

In this study, we use microsimulation modeling to estimate the net effects of excess deaths during the COVID pandemic on the OASDI program's expected future outlays, and we investigate the distribution of these changes across socioeconomic and race-ethnicity groups. Our analysis builds on extensive prior research using the Future Elderly Model (FEM) and the Future Adult Model (FAM), dynamic microsimulation models that have been applied to study a wide range of issues, including the future of Medicare (2) and the effects of chronic illnesses and risk factors such as diabetes, dementia, heart failure, obesity, serious mental illness, and smoking (3-8). These models have been extensively validated for quantity and quality of life, as well as specific risk factors and disease (9, 10). The FEM and FAM model OASDI retirement benefits and disability insurance benefits as a function of demographic, economic and health status variables, and they have previously been used to project COVID-19 mortality by demographic and health status (1). In addition, the FEM and FAM track the health and survival status of spouses, enabling us to project the effects of COVID-19 mortality on spousal survivors' benefits. In this study, we extend FAM to incorporate the presence of minor children eligible for survivors' benefits.

Estimating the effect of the pandemic-era mortality on OASDI finances using the FEM and FAM models helps inform SSA trust fund projections. Moreover, creating estimates by race-ethnicity helps to underscore not only the differential effects of COVID by race-ethnicity but also how different groups may rely on OASDI differently.

Our analysis combined death-record data with FEM and FAM microsimulation models to quantify the effect of excess deaths during the pandemic on life-cycle mortality and expected Social Security outlays for the US population ages 25 and over as of 2020. Our estimates account for the age, sex, and race-ethnicity of decedents based on CDC records, along with COVID-19 risk factors such as obesity, smoking behavior, lung disease, heart disease, diabetes, cancer, stroke, hypertension, dementia, and nursing home residence. We estimate that the 1.7 million pandemic-era excess deaths that occurred as of January 2023 reduced expected future OASDI outlays by $205 billion on net. This reduction is caused primarily by a decrease in future retirement benefits for pandemic decedents, which outweighs a reduction in OASDI payroll taxes and an increase of payments to surviving spouses and children. Non-Hispanic Black and Hispanic decedents leave behind more underage children per capita, and payments to their surviving family members are lower than for non-Hispanic White decedents, for all levels of educational attainment.

Methods

Excess death data

Weekly excess death data from the Centers for Disease Control and Prevention (CDC) were downloaded on July 18, 2023 and processed as described in Reif et al. (1). Deaths were pooled by quarter to account for seasonal variation. Excess deaths occurred between March 28, 2020 and January 21, 2023. This timeframe represents all weeks during which CDC found there to be excess deaths due to the pandemic, providing a complete dataset of excess COVID-19 pandemic mortality estimates. Since our previous publication (1), the CDC has updated its methodology for computing excess deaths. Initially, the CDC compared observed deaths to an expected baseline, computed using mortality data from 2013-2019. As the pandemic continued, however, the CDC switched to using rolling imputed baseline trends for 2020-2023 (11). The more recent excess death estimates, which we use in this paper, reflect this change.

Microsimulation

We used microsimulation to estimate life expectancy for a nationally representative set of adults using pre-pandemic data. Relying on methods developed in our prior publication (1), we computed the years of life lost from the pandemic. Specifically, we used empirical information on risk factors for COVID mortality to compute the likelihood of dying during the COVID pandemic. Within each age, sex, and race-ethnicity group, we assigned a COVID mortality risk score based on health comorbidities and other risk factors and distribute reported excess deaths proportionally. Non-COVID excess deaths were assigned using our regular mortality model estimates. The number of life-years lost is then calculated by computing the projected life expectancies of those who died as a result of the pandemic. Projections were constructed using two models, the FAM and the FEM. The FAM, which is based on data from the Panel Study for Income Dynamics (PSID), was used to model individuals who were ages 60 and under as of July 1, 2020. The FEM, which is based on data from the Health and Retirement Study (HRS), was used to model individuals who were over age 60 as of July 1, 2020. Full details about our microsimulation methodology are available in Reif et al. (1). Below, we describe the new outcomes reported in this study as well as adjustments that were made to the original methodology.

FAM and FEM simulations report results biennially, with each simulation wave covering a two-year period. However, to account for seasonal variation in excess deaths, quarterly mortality risk of simulants was preferred. Therefore, we interpolated biennial simulation outcomes to generate quarterly risk factor status for each simulant. This was accomplished by linear interpolation of continuous variables (age, BMI, and regular mortality probability) and by randomly assigning new onset of binary variables (new onset of diseases or changes in smoking status). Subsequently, weighted risk scores and excess deaths were assigned as described in detail by Reif et al. (1). The calibration to account for nursing home deaths was based on a total of 162,107 COVID-19-related deaths in nursing homes, as reported by the Centers for Medicare and Medicaid Services; risk scores for nursing home residents were adjusted to correctly represent quarterly death counts in nursing homes, before adjusting risk scores for community-dwelling simulants. Nursing home status was available in the FEM simulation for people 60 years and older.

Survivors' benefits

Data on children are necessary for accurately calculating survivors' benefits for pandemic decedents. Family and childbirth data were available only for FAM simulants, who are modeled using PSID data. Therefore, we cannot observe minor children of people who are 60 years or older on July 1st 2020, since these individuals are modeled using HRS data in FEM. For example, a newborn child of a 59-year-old would be included and followed to age 18 in our analysis, but a 17-year-old child of a 61-year-old adult would be excluded.

Data on the number of children and their birth years came from the PSID Individual file, which includes IDs for each parent. Children in PSID were dropped if they died after non-response; if they have been adopted by non-sample persons; if they were listed as spouses/cohabitors, ((great)grand)parents, uncles/aunts, (children of) 1st year cohabitors, or miscellaneous “other (non)relatives”; or if they were the reference person themselves. If birth year was missing, information from the PSID Childbirth and Adoption History (CAH) file was used instead. If it was missing from this file as well, birth year was imputed using an ordinary least squares regression model that included parent birth year, parent sex, adoption status of child, and year of last report, using CAH data after 1990. In cases where children were listed multiple times (for each parent in the PSID), we used the floor of the average predicted year of birth to fill in missing birth years.

Children and spouses who take care of a decedent’s child under 16 both generally receive 75% of a worker’s primary insurance amount (PIA), which is itself a function of average indexed monthly earnings (AIME). The family maximum is generally between 150-188% of the worker’s PIA. Calculations follow normal rules set by the Social Security Administration. Briefly, earnings are capped to maximum taxable wages (12) and indexed up to two years before the reference year (13). The AIME for survivors is calculated using a specified number of years of cumulative earnings, with fewer years included for younger decedents. This period starts from age 22, excludes the five lowest-earning years, and includes at least two and at most 35 years of earnings.

The amount of survivors’ benefits for decedents’ children and spouses taking care of children are calculated and assigned differently by age of the decedent. For those 60 years or older at time of death, we do not estimate benefits, since we do not have family data available to determine survivors’ beneficiaries after death. For those between the ages of 50 and 60, we used restricted Social Security covered earnings records from 2018, the most recent year of data available, from the Michigan Center on the Demography of Aging (MiCDA) data enclave. We determined the weighted median income by 5-year age bins, race-ethnicity (NH Black, Hispanic, NH White), gender, and education level (less than high school, high school graduate, BA+) for the 2018 HRS cohort, adjusted for inflation to years 2020 through 2023. We then calculated AIME and PIA based on respondents’ historical earnings data as described above and by standard SSA rules. The estimated survivors’ benefits and family maxima were exported from the enclave and assigned to decedents in the simulation based on the same demographic categories and year of death (2020-2023).

For decedents under age 50, we used population earnings from the PSID survey to determine AIME, PIA, and survivors' benefits, as PSID does not offer linked Social Security covered earnings data. Reported earnings histories are only available for years that a survey respondent is in the sample. We selected PSID respondents who were alive in 2019 and calculated the weighted median of their earnings reported for 2018 and earlier, by the same age/race-ethnicity/gender/education categories mentioned above. Biennial median earnings were then interpolated to construct yearly earnings, adjusted for inflation, and used as inputs to calculate AIME, PIA, survivors' benefits and family maxima. Benefits were then assigned based on the same demographic categories and year of death.

Survivors' benefits are subject to caps related to the earnings of the decedent's spouse and a family maximum. To compute the capped benefits, we first used PSID survey data to internally match spousal earnings to survey respondents, after adjusting for inflation to 2023 dollars. We then calculated weighted median spousal earnings by 5-year age bins, race (NH Black, Hispanic, NH White), and gender of the PSID respondents. The maximum reduction in spousal survivors' benefits was determined by dividing any median spousal earnings over the 2023 earnings limit of $21,240 by two, since the benefits are reduced by $1 for every $2 over the limit. These reductions were then applied to decedents based on the same demographic categories of the PSID respondents, and the survivors' benefits calculated earlier for spouses were reduced accordingly. Any negative values were treated as $0 benefits.

As with the survivors' benefits amount, the family maximum is also based on the decedent's PIA, following standard Social Security Administration rules. If a family's total amount of survivors' benefits exceeds their family maximum, the benefits are reduced proportionally for all family members.

We also compared the number of underage years for decedents' surviving children as a result of the pandemic to a counterfactual scenario in which the decedent would have lived for their projected life expectancy. Future children were simulated using transition models estimated on new childbirths in the survey data. In rare cases, a simulant who died in the pandemic but could have had children in the counterfactual scenario generated a negative number for this measure.

Earnings and OASDI tax

Earnings in FAM are derived from the PSID as a sum of wages and salaries, bonuses, overtime, tips, commissions, professional practice or trade, additional job income, and miscellaneous labor income (variable ER77315), plus the labor portion of business income (variable ER77296). Earnings in FEM are derived from the HRS as a sum of wage/salary income, bonuses/overtime pay/commissions/tips, 2nd job or military reserve earnings, and professional practice or trade income (RAND HRS variable iearn), and self-employment income (HRS FAT variable isemp)

In each survey wave, respondents reported their earnings from the previous year. Future earnings were simulated based on transition models developed separately for FAM and FEM, accounting for full-time or part-time employment, unemployment, out of labor force, or retirement. See the appendix for model specifications and coefficients. For years between waves, the earnings were interpolated and added to create two-year earnings totals, and adjusted for real wage growth using historical real wage differential data until 2020 (the start of the pandemic). For post-2020 earnings, intermediate projections are used (14). The final results are adjusted for inflation to 2023 dollar values.

OASDI tax was calculated as 12.4% of earnings. For employees, half of this tax (6.2%) is contributed by the employer, while self-employed individuals pay the full tax (12.4%) themselves. Only earnings up to the maximum taxable earnings are taxed. Recent limits are retrieved from the Social Security website (12); projected limits for years 2024-2032 are based on intermediate assumptions in the 2023 Annual Report of the Board of Trustees of the OASDI funds (15); and limits after 2032 are based on carrying forward a 3.9% percentage increase estimated for 2032.

Disability and retirement

Disability benefits for those under age 60 at the start of the pandemic were based on PSID survey questions regarding income from Social Security (variable ER77442) when Social Security type was disability (variable ER34812). This amount was then used to create transition models (see appendix for coefficients) to project future disability benefits using a two-step model for simulants predicted to receive those benefits.

Retirement benefits for those under age 60 at the start of the pandemic were also based on PSID survey questions regarding income from Social Security (variable ER77442), in this case when Social Security type was retirement, survivors' benefit, dependent of disabled recipient, dependent of retired recipient, or other (ER34813 through ER34817). This amount was then used to create transition models for the simulation (see appendix for coefficients) to project future retirement benefits using another two-step model for simulants predicted to retire. Prediction of claiming retirement benefits was limited to simulants not claiming disability benefits. Disability benefits were not assigned to those over 65.

Disability and retirement benefits for those over age 60 at the start of the pandemic were based on restricted Social Security earnings records from 2018 HRS respondents over age 50 obtained from the MiCDA enclave. We calculated AIME and quarters worked based on earnings histories following SSA standard rules, and we created joint estimation models (see appendix for model coefficients) for AIME and quarters worked. Model parameters were exported from the enclave and used to predict AIME and quarters worked for simulants, from which we calculated PIA and benefit amounts following SSA standard rules. Predictions of whether a person was disabled or retired (and subsequently was assigned a disability or retirement benefit amount, respectively) are based on public HRS data (RAND HRS variable ssdi for disability and ioss for retirement; see appendix for coefficients). Prediction of claiming retirement benefits was only done for simulants ages 62 and over who were not claiming disability benefits. Disability benefits were not assigned to those over age 65.

Table 1: Excess deaths and death rates between March 28th 2020 and January 21st 2023 during the COVID pandemic, by age (25+), sex, and race, based on weekly CDC data. Excess death rates are presented per 10,000 people in specific sex, age, race-ethnicity categories.

			Excess deaths			Excess death rate		
Race	**Sex**	**Age**	**COVID deaths**	**Non-COVID deaths**	**Total deaths**	**COVID death rate /10,000**	**Non-COVID death rate /10,000**	**Total death rate /10,000**
Non-Hispanic Black	Female	25-34	1,294	3,703	4,997	1	3	4
		35-44	2,909	4,731	7,640	3	4	7
		45-54	5,803	1,494	7,297	5	1	7
		55-64	12,684	6,375	19,059	12	6	18
		65-74	17,994	20,268	38,262	23	26	49
		75-84	16,449	11,959	28,408	46	33	79
		85+	15,264	7,648	22,912	104	53	157
	Male	25-34	1,487	10,706	12,193	1	8	9
		35-44	3,308	11,670	14,978	3	11	14
		45-54	7,649	7,483	15,132	8	8	16
		55-64	15,557	13,533	29,090	17	15	31
		65-74	20,872	28,177	49,049	36	47	83
		75-84	16,373	11,089	27,462	72	48	120
		85+	9,357	5,268	14,625	142	80	222
Hispanic	Female	25-34	1,137	2,127	3,264	1	1	2
		35-44	2,652	2,584	5,236	2	1	3
		45-54	5,572	2,803	8,375	4	2	6
		55-64	10,820	5,341	16,161	10	5	14
		65-74	14,934	9,471	24,405	22	13	35
		75-84	14,707	10,709	25,416	44	31	75
		85+	13,512	15,012	28,524	99	109	208
	Male	25-34	2,495	9,264	11,759	1	4	6
		35-44	6,636	10,873	17,509	4	6	9
		45-54	13,691	8,218	21,909	9	5	14
		55-64	21,654	12,160	33,814	20	11	31
		65-74	23,713	14,398	38,111	41	24	65
		75-84	18,981	9,767	28,748	80	40	120
		85+	12,054	7,884	19,938	161	105	266
Non-Hispanic White	Female	25-34	2,087	3,886	5,973	0	1	1
		35-44	5,299	10,809	16,108	1	2	3
		45-54	13,218	116	13,334	2	0	2
		55-64	34,586	15,662	50,248	5	2	8
		65-74	64,758	56,859	121,617	11	10	21
		75-84	90,690	71,976	162,666	29	22	51
		85+	131,245	7,569	138,814	91	5	96
	Male	25-34	3,206	11,422	14,628	1	2	2
		35-44	7,807	27,289	35,096	1	5	6
		45-54	22,005	4,122	26,127	4	1	5
		55-64	55,328	25,928	81,256	9	4	13
		65-74	97,783	85,831	183,614	19	17	36
		75-84	119,950	88,610	208,560	47	34	81
		85+	104,598	18,442	123,040	123	22	145
Total			1,062,118	693,236	1,755,354	46	30	76

Results

The pandemic resulted in 1,755,354 excess deaths of people over age 25, with the highest per capita rates for men, Black and Hispanic populations, and older age groups. This effect was observed for COVID deaths as well as excess deaths not attributed to COVID (here called non-COVID deaths) (**Table 1**). Considerable fluctuations are present over time, with different proportions of the quarterly excess deaths attributed to different age groups or cause (**Figure 1**).

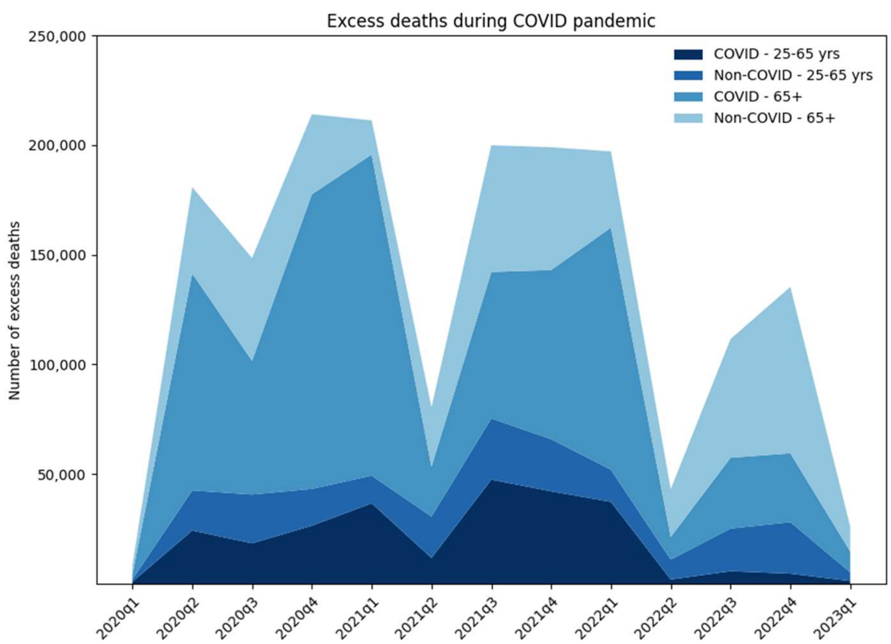


Figure 1: Excess deaths by quarter, cause of death, and age group (under and over 65 years), based on weekly CDC data.

Over one-third of pandemic decedents (36%) were estimated to receive employment or self-employment income at the time of death (**Table 2**). About 4% were receiving disability benefits, and 71% were receiving OASDI benefits. These categories are not mutually exclusive. Decedents who were working lost on average 23.7 life years, of which 9.6 years would have been spent working, 0.5 years receiving disability benefits, and 14.4 years receiving retirement benefits. Without the pandemic, this group would have paid $89K in OASDI tax and would have received $8K and $203K in disability and retirement benefits, respectively (in $2023, discounted).

The 72K decedents receiving disability benefits at time of death were slightly younger (56.7 years vs. 58.5 years for those who were working) and had a counterfactual life expectancy of 18.7 years, of which 4.6 years would have been spent working, 3.2 years on disability, and 11.8 years in retirement. Without the pandemic, these decedents would have paid $34k in OASDI tax and received $55k and $121k in disability and retirement benefits, respectively (in $2023, discounted).

Over 1.2 million people were receiving retirement benefits when they died, and were on average the oldest decedents at 79.2 years. They lost 9.0 years of life due to the pandemic, of which 0.8 years would have been working years and 8.1 years would have been in retirement. Their time spent receiving disability benefits was negligible. Without the pandemic, this group would have paid $3k in OASDI tax, and received $300 and $184k in disability and retirement benefits, respectively (in $2023, discounted; **Table 2**).

The pandemic also resulted in 313K additional beneficiaries, including 243K surviving children under 18 and 70K surviving spouses caring for decedents' children under 16 years of age (**Table 3**). Among decedents who were 60 at time of death with children under 18, each had on average 1.5 children under 18, and 42% had a spouse caring for their children under 16. On average, surviving children and spouses will receive 8.4 years and 7.5 years of benefits, with lifetime benefit amounts of $121K and $58K, respectively ($2023, discounted).

Table 2: Average amount decedents would have received (disability or retirement benefits) or paid (OASDI payroll taxes) in the counterfactual scenario, in 2023$. Decedents are categorized by their employment or benefit status at time of death; categories are not mutually exclusive. Values in parentheses are 95% confidence intervals.

During pandemic	Number of decedents (95% CI) [%]	Avg age at death (yrs)	Avg life years lost		Avg number of years in future	Avg lifetime $ x 1000, 3% disc.	Avg lifetime $ x 1000
Received employment or self-employment income	636,719			Earnings:	9.6 (9.3 - 9.9)	+89 (86 - 93)*	+130 (124 - 136)*
	(629,734 - 643,704)	58.5 (58.4 - 58.7)	23.7 (23.3 - 24.2)	Disability:	0.5 (0.4 - 0.5)	-8 (7 - 9)	-12 (10 - 13)
	[36%]			Retirement:	14.4 (14.0 - 14.7)	-203 (199 - 206)	-311 (303 - 318)
Received disability benefits	71,961			Earnings:	4.6 (4.3 - 5.0)	+34 (31 - 38)*	+48 (42 - 53)*
	(67,946 - 75,976)	56.7 (56.3 - 57.0)	18.7 (18.2 - 19.2)	Disability:	3.2 (3.1 - 3.4)	-55 (51 - 59)	-61 (56 - 66)
	[4%]			Retirement:	11.8 (11.3 - 12.2)	-121 (116 - 126)	-187 (180 - 195)
Received retirement benefits (>62 yrs)	1,251,720			Earnings:	0.8 (0.7 - 0.8)	+3 (2 - 3)*	+3 (3 - 3)*
	(1,248,981 - 1,254,458)	79.2 (79.2 - 79.3)	9.0 (8.9 - 9.1)	Disability:	0.01 (0.01 - 0.01)	-0.3 (0.3 - 0.3)	-0.3 (0.3 - 0.3)
	[71%]			Retirement:	8.1 (8.0 - 8.2)	-184 (182 - 186)	-221 (218 - 224)

* OASDI tax, calculated as 12.4% of (self-employment) earnings. Amounts not paid because of death

Table 3: Average benefit amounts for surviving children, and spouses who care for child(ren) of decedents, in 2023$. Values in parentheses are 95% confidence intervals.

During pandemic	Number of survivors (1000s)	Avg number of survivors receiving benefits (per decedent)**	Avg number years of benefits	Avg lifetime benefit amount x1000, 3% disc. (per survivor)	Avg lifetime benefit amount x1000 (per survivor)
Child(ren) under 18*	243 (234 - 251)	1.47 (1.44 - 1.51)	8.4 (8.3 - 8.4)	121 (119 - 122)	137 (135 - 138)
(Divorced) spouse with decedent's child(ren) under 16*	70 (67 - 73)	0.42 (0.41 - 0.44)	7.5 (7.3 - 7.7)	58 (56 - 60)	65 (63 - 68)

* Not including those not eligible for benefits or with $0 benefits (e.g. after reduction based on earnings limit for spouse)

** Among decedents with children under 18 at time of death

Table 4: Aggregate OASDI amounts for pandemic decedents, in 2023$. Values in parentheses are 95% confidence intervals.

	Undiscounted		3% discounted	
	Decreases OASDI fund	Increases OASDI fund	Decreases OASDI fund	Increases OASDI fund
OASDI payroll/SE taxes not received	$84 billion (80 - 88)		$58 billion (56 - 60)	
Benefits for surviving (spouses with) children	$36 billion (34 - 38)		$32 billion (31 - 33)	
Unpaid disability benefits		$9 billion (8 - 10)		$7 billion (6 - 8)
Unpaid retirement benefits		$385 billion (378 - 392)		$287 billion (283 - 291)
Total effect on OASDI fund	$274 billion (267 - 281)		$205 billion (200 - 209)	

Overall, excess deaths during the pandemic have a net positive effect on the OASDI fund, mostly because of a reduction in future retirement benefits ($287 billion) that no longer need to be paid to decedents (**Table 4**). This gain was partially offset by new survivors' benefits (-$32 billion) and OASDI payroll taxes (-$58 billion) that will not be received in the future from decedents who were working at the time of their death. The reduction in disability benefits also offsets the gain, but only by a small amount ($7 billion). The total net gain for the OASDI fund is $205 billion ($2023, discounted, **Table 4**).

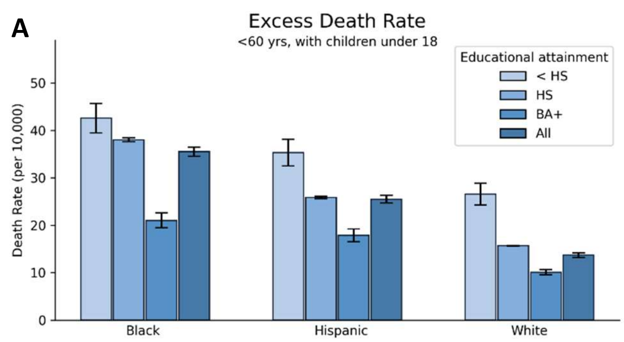
When examining aggregate effects on the OASDI fund by race-ethnicity, the largest share of this gain (83.6%) comes from NH White decedents, who comprised 67.3% of excess deaths (**Table 5**). NH Black and Hispanic decedents account for 11.3% and 5.0% of the net effect on the OASDI fund, with approximately equal shares of excess deaths (16.6% and 16.1% respectively). The net effect for decedents with children under 18 is negative, primarily because of new survivors' benefits. Conversely, the net effect for groups of decedents without children under 18 is positive, driven primarily by unpaid retirement benefits. For both groups, the negative and positive effects are relatively smaller for Black and Hispanic decedents than for White decedents with respect to the share of excess deaths these groups represent.

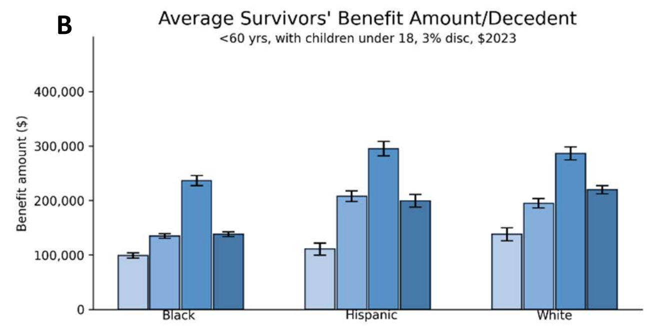
Table 5: Excess deaths and net effects on the OASDI funds by race-ethnicity, for decedents with and without children under 18. Dollar amounts in 2023$, 3% discounted. Values in parentheses are 95% confidence intervals.

		Non-Hispanic Black	Hispanic	Non-Hispanic White
Without children	Excess deaths, absolute	253,002 (252,262 - 253,742)	233,240 (231,910 - 234,570)	1,104,437 (1,102,601 - 1,106,273)
	Excess deaths, % of total	14.4% (14.4 - 14.5)	13.3% (13.2 - 13.4)	62.9% (62.8 - 63.0)
	Net effect on OASDI fund	$29.3 billion (28.3 - 30.2)	$24.4 billion (23.6 - 25.1)	$195.8 billion (193.2 - 198.5)
With children	Excess deaths, absolute	38,102 (37,362 - 38,842)	49,929 (48,599 - 51,259)	76,644 (74,808 - 78,480)
	Excess deaths, % of total	2.2% (2.1 - 2.2)	2.8% (2.8 - 2.9)	4.4% (4.3 - 4.5)
	Net effect on OASDI fund	$-6.2 billion (-6.9 - -5.4)	$-14.2 billion (-15.2 - -13.2)	$-24.5 billion (-26.2 - -22.9)
All	Excess deaths, absolute	291,104 (291,104 - 291,104)	283,169 (283,169 - 283,169)	1,181,081 (1,181,081 - 1,181,081)
	Excess deaths, % of total	16.6% (16.6 - 16.6)	16.1% (16.1 - 16.1)	67.3% (67.3 - 67.3)
	Net effect on OASDI fund	$23.1 billion (21.6 - 24.6)	$10.2 billion (8.7 - 11.6)	$171.3 billion (168.0 - 174.6)
	Net effect on OASDI fund, % of total	11.3% (10.7 - 11.9)	5.0% (4.3 - 5.6)	83.8% (83.0 - 84.5)

Although the White population as a whole represented a larger share of excess deaths, the per capita excess death rate was higher among Black and Hispanic populations, as well as those with lower educational attainment (**Figure 2A**). Educational attainment and race-ethnicity were also significantly associated with survivors' benefits for decedents' children. For decedents without a high school degree, total family benefits were lower for Black and Hispanic decedents than for White decedents. For those with a high school degree or more, total family benefits were lower for Black decedents than for Hispanic and White decedents (**Figure 2B**).

Because survivors' benefits have a family maximum based on the decedent's PIA, and the decedent's age and average number of children per decedent are lower for Black decedents (**Table 6**), we also estimated the benefit amount per child. For every educational level, the average benefits were lowest for surviving children of both Black and Hispanic decedents, compared to White decedents (**Figure 2C**). Thus, Black decedents' families received the lowest amount of (family) benefits while experiencing the highest excess death rates. For Hispanic decedents, survivors' benefit amounts were more similar to Black or White decedents depending on the measure used (child versus family) and educational attainment, with excess death rates falling between the two groups.





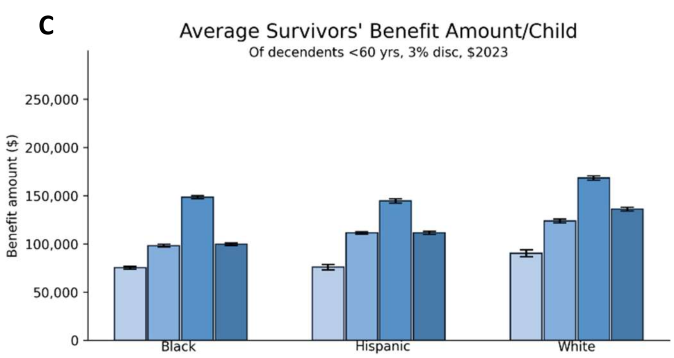


Figure 2: Disparities in survivors' benefits by education and race-ethnicity. Subsample includes decedents under 60 years with children under 18 at time of death. (A) Excess death rate. (B) Average survivors' benefit amount per decedent. (C) Average survivors' benefit amount per child. Error bars represent 95% confidence intervals.

In addition to the racial-ethnic disparities in survivors' benefits, the higher excess death rates among Black and Hispanic populations resulted in a longer average duration that decedents' children have left before reaching 18 years of age, on a per capita basis (**Figure 3**). Children of Black, Hispanic, and White decedents have on average 29.4, 19.5 and 12.1 years left per 1,000 children in the general population. As a result of the pandemic, we estimate that 262K children under age 18 lost a parent, including 56K from

Black decedents, 84K from Hispanic decedents, and 122K from White decedents. The average age at death for decedents with underage children was only slightly lower for the Black population (41.0 years) versus Hispanic (42.4 years) and White (42.5 years). However, Hispanic and White decedents with underage children had on average more children per decedent (1.69 and 1.60, respectively) than Black decedents (1.46).

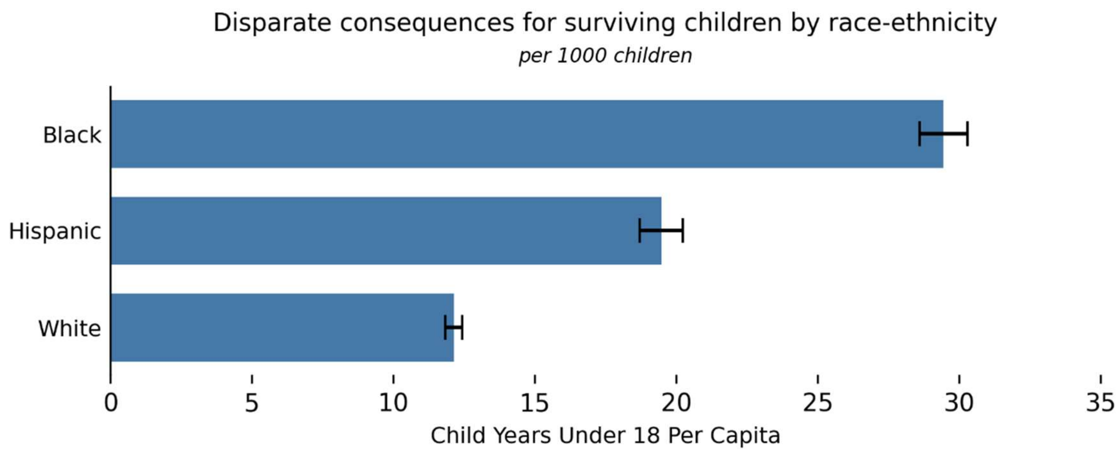


Figure 3: Black and Hispanic decedents leave behind more underage children per capita, illustrated by the average number of years left before a child of a decedent reaches age 18 (per 1000 children).

Table 6: The estimated number of children with a deceased parent as a result of the pandemic, the average age of the deceased parent, and the average number of children per deceased parent. Rates are among simulated decedents under 60 with any children under 18, by race-ethnicity

	Number of children with deceased parent (1000s)	Average age of decedent	Average number of children/decedent
Non-Hispanic Black	56 (54 - 58)	41.0 (40.9 - 41.2)	1.46 (1.43 - 1.49)
Hispanic	84 (80 - 89)	42.4 (42.3 - 42.5)	1.69 (1.63 - 1.75)
Non-Hispanic White	122 (117 - 128)	42.5 (42.4 - 42.6)	1.60 (1.56 - 1.64)

Discussion

From an actuarial standpoint, the excess deaths during the COVID-19 pandemic reduced the liabilities of the OASDI system by $205 billion, or $117K per decedent, on net. The reduction in benefit payouts outweighed the loss of future tax revenues from decedents and new payments of survivors' benefits to decedents' families. However, these public fiscal benefits are extremely modest compared to the broader costs generated by the COVID-19 pandemic.

Our analysis suggests a slight improvement in Social Security's financial health due to excess deaths, driven primarily by the premature death of people who would have received retirement benefits. Offsetting effects, such as the increase in survivors' insurance beneficiaries, are relatively small by comparison. Although the effect of a parent's premature death on the (financial) wellbeing of a family is devastating, only 9.4% of pandemic decedents were estimated to have children under 18 at the time of death. We estimate that 262K children lost a parent in 34 months (7.7K/month) of the pandemic, which aligns closely with a previous estimate of 105K in the first 14 months of the pandemic (7.5K/month) (16). In addition to this component being relatively small, benefits for surviving spouses and children are likely overestimated, since a large fraction of children with a deceased parent do not claim these benefits (Weaver, 2019). The other components of our analysis, such as the reduction in the OASDI tax receipts or the discontinuation of retirement and disability benefits, are more likely to be realized. If none of the eligible survivors claimed their benefits, the net effect of excess deaths on the OASDI fund could be up to $32 billion (16%) larger.

That said, the effects on Social Security could also be worse than we forecast, because we do not account for the possible effects of morbidity, such as long COVID. However, it seems unlikely that this omission would reverse our qualitative finding that the excess deaths improved the solvency of Social Security. As of September 2022, approximately 420,000 people (or 0.3% of the workforce) were estimated to have left the workforce due to long-COVID (17). Given that the average yearly disability benefit is $17,797 (18), each former worker would need to claim disability benefits for 37 years to completely offset the net fiscal effect we find. Additionally, Goda et al. (19) reported that disability benefit applications actually decreased in the first two years of the pandemic, and only partially recovered to pre-pandemic levels after the expiration of generous unemployment benefit programs. This suggests that long COVID-related disability is unlikely to substantially affect OASDI finances.

Our findings align with early projections in the 2021 Trustees Report (20), which suggested that excess or premature mortality would increase the projected trust fund ratio and have a positive impact on the solvency. Despite this projection, other factors—such as temporary and permanent reductions in employment, GDP, productivity, earnings, birth rates, and new disability applications—led to a reduction in the overall insolvency by one year, with a projected depletion year of 2034. Subsequent Trustees reports (21-23) adjusted the depletion year to 2035, then 2034, and back to 2035. The latest report from 2024 continues to assume no significant long-term effect of the pandemic on the OASDI fund's solvency.

Our analysis included retired workers, spouses of retired workers, children of deceased workers, widowed mothers/fathers, and disabled workers. Together, these groups comprise 91.4% of beneficiaries and 93.4% of total monthly benefits (24). Several smaller groups were not included in the calculation of the effect of pandemic excess deaths on the OASDI fund. We excluded children of retired workers (1% of beneficiaries) because we were not able to assess whether a child was receiving retirement benefits based on the parent's account and/or whether they were disabled. We also excluded nondisabled and disabled widow(er)s (5.3% and 0.3%) because we were not able to determine whether surviving spouses of deceased workers would receive additional benefits above and beyond their own worker/spousal/disability benefits, and because we lack data on whether widowed spouses would remarry before 60, change financial or career trajectories after experiencing widowhood, or have changes in their disability status. We also excluded spouses and children of disabled workers (0.1% and 1.7%) because we did not have data on whether spouses and children of disabled workers were collecting additional disability insurance benefits. Finally, we excluded parents of deceased workers (0.001%), a group that consists of fewer than 1000 people. While these groups were excluded, they represent a small fraction of beneficiaries. Overall, our analysis captures the major OASDI beneficiary categories, covering the large majority of recipients, to determine the net effect of excess deaths on the OASDI fund.

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The Future Adult Model: Technical Documentation

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This appendix describes technical details to support the paper **”The Effect of US COVID-19 Excess Mortality on Social Security Outlays”**.

1 Functioning of the dynamic model

1.1 Background

The Future Elderly Model (FEM) is a microsimulation model originally developed out of an effort to examine health and health care costs among the elderly Medicare population (age 65+). A description of the previous incarnation of the model can be found in Goldman et al. (2004). The original work was founded by the Centers for Medicare and Medicaid Services and carried out by a team of researchers composed of Dana P. Goldman, Paul G. Shekelle, Jayanta Bhattacharya, Michael Hurd, Geoffrey F. Joyce, Darius N. Lakdawalla, Dawn H. Matsui, Sydne J. Newberry, Constantijn W. A. Panis and Baoping Shang.

Since then various extensions have been implemented to the original model. The most recent version of the FEM now projects health outcomes for all Americans aged 51 and older and uses the

Health and Retirement Study (HRS) as a host dataset rather than the Medicare Current Beneficiary Survey (MCBS). The work has also been extended to include economic outcomes such as earnings, labor force participation and pensions. This work was funded by the National Institute on Aging through its support of the RAND Roybal Center for Health Policy Simulation (P30AG024968), the Department of Labor through contract J-9-P-2-0033, the National Institutes of Aging through the R01 grant "Integrated Retirement Modeling" (R01AG030824) and the MacArthur Foundation Research Network on an Aging Society.

This document describes the Future Adult Model (FAM), the development of the model to forecast Americans aged 25 and older. FAM uses the Panel Survey of Income Dynamics (PSID) as the host dataset. In addition to modeling health, health care costs, and economic outcomes, FAM also models life events such as changes in marital status and childbearing. Development of FAM is supported by the National Institutes of Aging through the USC Roybal Center for Health Policy Simulation (5P30AG024968-13) and the MacArthur Foundation Research Network on an Aging Society.

1.2 Overview

The defining characteristic of the model is the modeling of real rather than synthetic cohorts, all of whom are followed at the individual level. This allows for more heterogeneity in behavior than would be allowed by a cell-based approach. Also, since the PSID interviews both respondent and spouse, we can link records to calculate household-level outcomes, which depend on the responses of both spouses.

The model has three core components:

- The replenishing cohort module predicts the economic and health outcomes of new cohorts of 25/26 year-olds. This module takes in data from the Panel Survey of Income Dynamics (PSID) and trends calculated from other sources. It allows us to "generate" cohorts as the simulation proceeds, so that we can measure outcomes for the age 25+ population in any given year.

- The transition module calculates the probabilities of transiting across various health states and financial outcomes. The module takes as inputs risk factors such as smoking, weight, age and education, along with lagged health and financial states. This allows for a great deal of heterogeneity and fairly general feedback effects. The transition probabilities are estimated from the longitudinal data in the PSID.

- The policy outcomes module aggregates projections of individual-level outcomes into policy outcomes such as taxes, medical care costs, and disability benefits. This component takes account of public and private program rules to the extent allowed by the available outcomes.

Figure 1 provides a schematic overview of the model. In this example, we start in 2014 with an initial population aged 25+ taken from the PSID. We then predict outcomes using our estimated transition probabilities (see section 3.1). Those who survive make it to the end of that year, at which point we calculate policy outcomes for the year. We then move to the following time period (two years later), when a replenishing cohort of 25 and 26 year-olds enters (see section 4). This entrance forms the new age 25+ population, which then proceeds through the transition model as before. This process is repeated until we reach the final year of the simulation.

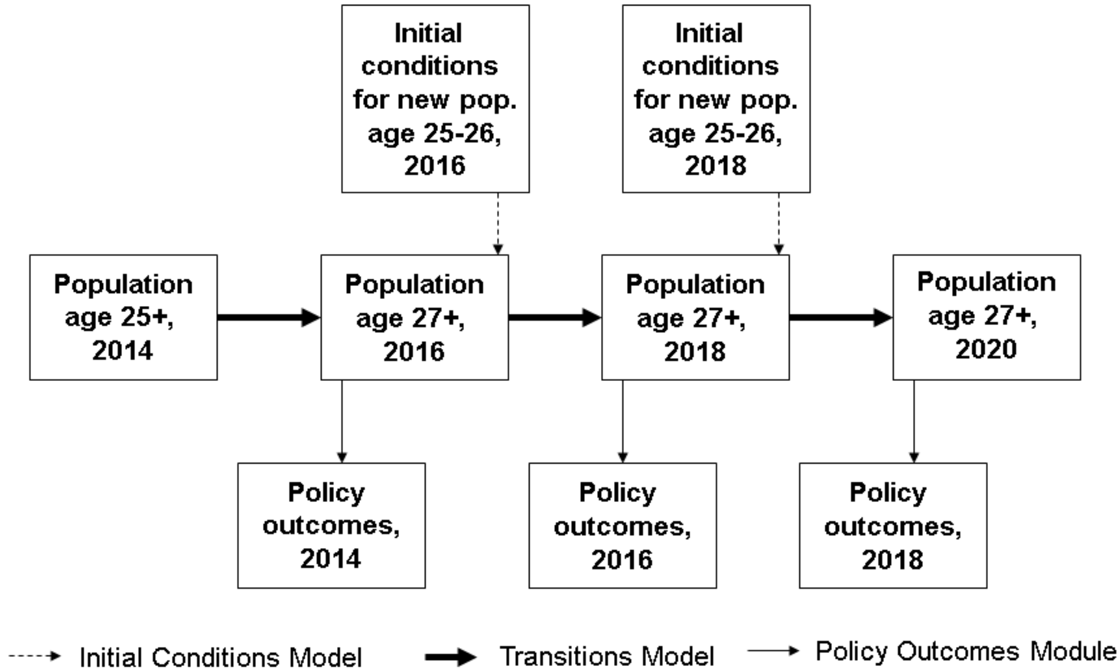

Figure 1: Architecture of the FAM

1.3 Comparison with other microsimulation models of health expenditures

The precursor to the FAM, the FEM, was unique among models that make health expenditure projections. It was the only model that projected health trends rather than health expenditures. It was also unique in generating mortality projections based on assumptions about health trends rather than historical time series.

FAM extends FEM to younger ages, adding additional dimensions to the simulation. Events over the life course, such as marital status and childbearing are simulated. Labor force participation is modeled in greater detail, distinguishing between out-of-labor force, unemployed, working part-time, and working full-time.

1.3.1 CBOLT Model

The Congressional Budget Office (CBO) uses time-series techniques to project health expenditure growth in the short term and then makes an assumption on long-term growth. They use a long term growth of excess costs of 2.3 percentage points starting in 2020 for Medicare. They then assume a reduction in excess cost growth in Medicare of 1.5% through 2083, leaving a rate of 0.9% in 2083. For non-Medicare spending they assume an annual decline of 4.5%, leading to an excess growth rate in 2083 of 0.1%.

1.3.2 Centers for Medicare and Medicaid Services

The Centers for Medicare and Medicaid Services (CMS) performs an extrapolation of medical expenditures over the first ten years, then computes a general equilibrium model for years 25 through 75 and linearly interpolates to identify medical expenditures in years 11 through 24 of their estimation. The core assumption they use is that excess growth of health expenditures will be one percentage point higher per year for years 25-75 (that is if nominal GDP growth is 4%, health care expenditure growth will be 5%).

1.3.3 MINT Model

Modeling Income in the Near Term (MINT) is a microsimulation model developed by the Urban Institute and others for the Social Security Administration to enable policy analysis of proposed changes to Social Security benefits and payroll taxes Smith and Favreault (2013). MINT uses the Survey of Income and Program Participation (SIPP) as the base data and simulates a range of outcomes, with a focus on those that will impact Social Security. Recent extensions have included health insurance coverage and out-of-pocket medical expenditures. Health enters MINT via self-reported health status and self-reported work limitations. MINT simulates marital status and fertility.

2 Data sources used for estimation

The Panel Survey of Income Dynamics is the main data source for the model. We estimate models for assigning characteristics for the replacement cohorts in Replenishing Conditions Module. These are summarized in Table 1. We estimate transition models for the entire PSID population in the Transition Model Module. Transitioned outcomes are described in Table 2.

2.1 Panel Survey of Income Dynamics

The Panel Survey of Income Dynamics (PSID), waves 1999-2019 are used to estimate the transition models. PSID interviews occur every two years. We create a dataset of respondents who have formed their own households, either as single heads of households, cohabitating partners, or married partners. These heads, wives, and "wives" (males are automatically assigned head of household status by the PSID if they are in a couple) respond to the richest set of PSID questions, including the health questions that are critical for our purposes.

We use all respondents age 25 and older. When appropriately weighted, the PSID is representative of U.S. households. We also use the PSID as the host data for full population simulations that begin in 2009. Respondents age 25 and 26 are used as the basis for the synthetic cohorts that we generate, used for replenishing the sample in population simulations or as the basis of cohort scenarios.

The PSID continually adds new cohorts that are descendents (or new partners/spouses of descendents). Consequently, updating the simulation to include more recent data is straightforward.

2.2 Health and Retirement Study

The Health and Retirement Study (HRS), waves 1998-2018 are pooled with the PSID for estimation of mortality and widowhood models. The HRS has a similar structure to the PSID, with interviews occurring every two years. The HRS data is harmonized to the PSID for all relevant variables. We use the dataset created by RAND (RAND HRS, version 1992-2018v2) as our basis for the analysis. We use all cohorts in the analysis. When appropriately weighted, the HRS in 2016 is representative of U.S. households where at least one member is at least 51. Compared to the PSID, the HRS includes more older Hispanics and interviews more respondents once they have entered nursing homes.

3 Estimation

In this section we describe the approach used to estimate the transition model, the core of the FAM, and the initial cohort model which is used to rejuvenate the simulation population.

3.1 Transition model

We consider a large set of outcomes for which we model transitions. Table 5 gives the set of outcomes considered for the transition model along with descriptive statistics and the population at risk when estimating the relationships.

Since we have a stock sample from the age 25+ population, each respondent goes through an individual-specific series of intervals. Hence, we have an unbalanced panel over the age range starting from 25 years old. Denote by j_{i0} the first age at which respondent i is observed and j_{iT_i} the last age when he is observed. Hence we observe outcomes at ages $j_i = j_{i0}, \ldots, j_{iT_i}$.

We first start with discrete outcomes which are absorbing states (e.g. disease diagnostic, mortality, benefit claiming). Record as $h_{i,j_i,m} = 1$ if the individual outcome m has occurred as of age j_i. We assume the individual-specific component of the hazard can be decomposed in a time invariant and variant part. The time invariant part is composed of the effect of observed characteristics x_i that are constant over the entire life course and initial conditions $h_{i,j_0,-m}$ (outcomes other than the outcome m) that are determined before the first age in which each individual is observed The time-varying part is the effect of previously diagnosed outcomes $h_{i,j_i-1,-m}$, on the hazard for m.[1] We assume an index of the form $z_{m,j_i} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + h_{i,j_0,-m}\psi_m$. Hence, the latent component of the hazard is modeled as

$$h^*_{i,j_i,m} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + h_{i,j_0,-m}\psi_m + a_{m,j_i} + \varepsilon_{i,j_i,m}, \quad (1)$$

$$m = 1, \ldots, M_0,\ j_i = j_{i0}, \ldots, j_{i,T_i},\ i = 1, \ldots, N$$

The term $\varepsilon_{i,j_i,m}$ is a time-varying shock specific to age j_i. We assume that this last shock is normally distributed and uncorrelated across diseases. We approximate a_{m,j_i} with an age spline with knots at ages 35, 45, 55, 65, and 75. This simplification is made for computational reasons since the joint estimation with unrestricted age fixed effects for each condition would imply a large number of parameters. The absorbing outcome, conditional on being at risk, is defined as

$$h_{i,j_i,m} = \max\{I(h^*_{i,j_i,m} > 0), h_{i,j_i-1,m}\}$$

The occurrence of mortality censors observation of other outcomes in a current year.

A number of restrictions are placed on the way feedback is allowed in the model. Table 6 documents restrictions placed on the transition model. We also include a set of other controls. A list of such controls is given in Table 7 along with descriptive statistics.

We have five other types of outcomes:

1. First, we have binary outcomes which are not an absorbing state, such as starting smoking. We specify latent indices as in (1) for these outcomes as well but where the lag dependent outcome also appears as a right-hand side variable. This allows for state-dependence.

2. Second, we have ordered outcomes. These outcomes are also modeled as in (1) recognizing the observation rule is a function of unknown thresholds ς_m. Similarly to binary outcomes, we allow for state-dependence by including the lagged outcome on the right-hand side.

[1] With some abuse of notation, $j_i - 1$ denotes the previous age at which the respondent was observed.

3. The third type of outcomes we consider are censored outcomes, such as financial wealth. For wealth, there are a non-negligible number of observations with zero and negative wealth. For these, we consider two part models where the latent variable is specified as in (1) but model probabilities only when censoring does not occur. In total, we have M outcomes.

4. The fourth type of outcomes are continuous outcomes modeled with ordinary least squares. For example, we model transitions in log(BMI). We allow for state-dependence by including the lagged outcome on the right-hand side.

5. The final type of models are categorical, but without an ordering. For example, an individual can transition to being out of the labor force, unemployed, or working (either full- or part-time). In situations like this, we utilize a multinomial logit model, including the lagged outcome on the right-hand side.

The parameters $\theta_1 = \left(\{\beta_m, \gamma_m, \psi_m, \varsigma_m\}_{m=1}^{M},\right)$, can be estimated by maximum likelihood. Given the normality distribution assumption on the time-varying unobservable, the joint probability of all time-intervals until failure, right-censoring or death conditional on the initial conditions $h_{i,j_0,-m}$ is the product of normal univariate probabilities. Since these sequences, conditional on initial conditions, are also independent across diseases, the joint probability over all disease-specific sequences is simply the product of those probabilities.

For a given respondent observed from initial age j_{i0} to a last age j_{T_i}, the probability of the observed health history is (omitting the conditioning on covariates for notational simplicity)

$$l_i^{-0}(\theta; h_{i,j_{i0}}) = \left[\prod_{m=1}^{M-1}\prod_{j=j_{i1}}^{j_{T_i}} P_{ij,m}(\theta)^{(1-h_{ij-1,m})(1-h_{ij,M})}\right] \times \left[\prod_{j=j_{i1}}^{j_{T_i}} P_{ij,M}(\theta)\right]$$

We use the -0 superscript to make explicit the conditioning on $\mathbf{h}_{i,j_{i0}} = (h_{i,j_{i0},0}, \ldots, h_{i,j_{i0},M})'$. We have limited information on outcomes prior to this age. The likelihood is a product of M terms with the mth term containing only $(\beta_m, \gamma_m, \psi_m, \varsigma_m)$. This allows the estimation to be done separately for each outcome.

3.1.1 Further Details on Specific Transition Models

This section describes the modeling strategy for particular outcomes.

Employment Status Ultimately, we wish to simulate if an individual is out of the labor force, unemployed, working part-time, or working full-time at time t. We treat the estimation of this as a two-stage process. In the first stage, we predict if the individual is out of the labor force, unemployed, or working for pay using a multinomial logit model. Then, conditional on working for pay, we estimate if the individual is working part- or full-time using a probit model.

Earnings We estimate last calendar year earnings models based on the current employment status, controlling for the prior employment status. Of particular concern are individuals with no earnings, representing approximately twenty-five percent of the unemployed and seventy-eight percent of those out of the labor force. This group is less than 0.5% of the full- and part-time populations. We use a two-stage process for those out of the labor force and unemployed. The first stage is a probit that estimates if the individual has any earnings. The second stage is an OLS model of log(earnings) for those with non-zero earnings. For those working full- or part-time, we estimate OLS models of log(earnings).

Relationship Status We are interested in three relationship statuses: single, cohabitating, and married. In each case, we treat the transition from time t to time $t+1$ as a two-stage process. In the first stage, we estimate if the individual will remain in their current status. In the second stage, we estimate which of the two other states the individual will transition to, conditional on leaving their current state.

Childbearing We estimate the number of children born in two-years separately for women and men. We model this using an ordered probit with three categories: no new births, one birth, and two births. Based on the PSID data, we found the exclusion of three or more births in a two-year period to be appropriate.

3.1.2 Inverse Hyperbolic Sine Transformation

One problem fitting the wealth distribution is that it has a long right tail and some negative values. We use a generalization of the inverse hyperbolic sine transform (IHT) presented in MacKinnon and Magee (1990). First denote the variable of interest y. The hyperbolic sine transform is

$$y = \sinh(x) = \frac{\exp(x) - \exp(-x)}{2} \tag{2}$$

The inverse of the hyperbolic sine transform is

$$x = \sinh^{-1}(y) = h(y) = \log(y + (1 + y^2)^{1/2})$$

Consider the inverse transformation. We can generalize such transformation, first allowing for a shape parameter θ,

$$r(y) = h(\theta y)/\theta \tag{3}$$

Such that we can specify the regression model as

$$r(y) = x\beta + \varepsilon, \varepsilon \sim \mathrm{N}(0, \sigma^2) \tag{4}$$

A further generalization is to introduce a location parameter ω such that the new transformation becomes

$$g(y) = \frac{h(\theta(y + \omega)) - h(\theta\omega)}{\theta h'(\theta\omega)} \tag{5}$$

where $h'(a) = (1 + a^2)^{-1/2}$.

We specify (4) in terms of the transformation g. The shape parameters can be estimated from the concentrated likelihood for θ, ω. We can then retrieve β, σ by standard OLS.

Upon estimation, we can simulate

$$\tilde{g} = x\hat{\beta} + \sigma\tilde{\eta}$$

where η is a standard normal draw. Given this draw, we can retransform using (5) and (2)

$$h(\theta(y + \omega)) = \theta h'(\theta\omega)\tilde{g} + h(\theta\omega)$$

$$\tilde{y} = \frac{\sinh\left[\theta h'(\theta\omega)\tilde{g} + h(\theta\omega)\right] - \theta\omega}{\theta}$$

The included estimates table (estimates_FAM.xml) gives parameter estimates for the transition models.

4 Model for replenishing cohorts

We first discuss the empirical strategy, then present the model and estimation results. The model for replenishing cohorts integrates information coming from trends among younger cohorts with the joint distribution of outcomes in the current population of age 25 respondents in the PSID.

4.1 Model and estimation

Assume the latent model for $\mathbf{y}_i^* = (y_{i1}^*, \ldots, y_{iM}^*)'$,

$$\mathbf{y}_i^* = \mu + \varepsilon_i,$$

where ε_i is normally distributed with mean zero and covariance matrix $\mathbf{\Omega}$. It will be useful to write the model as

$$\mathbf{y}_i^* = \mu + \mathbf{L}_\Omega \eta_i,$$

where $\mathbf{L}_\Omega$ is a lower triangular matrix such that $\mathbf{L}_\Omega \mathbf{L}_\Omega' = \mathbf{\Omega}$ and $\eta_i = (\eta_{i1}, \ldots, \eta_{iM})'$ are standard normal. We observe $y_i = \Gamma(y_i^*)$ which is a non-invertible mapping for a subset of the M outcomes. For example, we have binary, ordered and censored outcomes for which integration is necessary.

The vector μ can depend on some variables which have a stable distribution over time $\mathbf{z}_i$ (say race, gender and education). This way, estimation preserves the correlation with these outcomes without having to estimate their correlation with other outcomes. Hence, we can write

$$\mu_i = \mathbf{z}_i \beta$$

and the whole analysis is done conditional on $\mathbf{z}_i$.

For binary and ordered outcomes, we fix $\Omega_{m,m} = 1$ which fixes the scale. Also we fix the location of the ordered models by fixing thresholds as $\tau_0 = -\infty$, $\tau_1 = 0$, $\tau_K = +\infty$, where K denotes the number of categories for a particular outcome. We also fix to zero the correlation between selected outcomes (say earnings) and their selection indicator. Hence, we consider two-part models for these outcomes. Because some parameters are naturally bounded, we also re-parameterize the problem to guarantee an interior solution. In particular, we parameterize

$$\begin{aligned}
&\Omega_{m,m} = \exp(\delta_m), \ m = m_0 - 1, \ldots, M \\
&\Omega_{m,n} = \tanh(\xi_{m,n})\sqrt{\Omega_{m,m}\Omega_{m,n}}, \ m, n = 1, \ldots, N \\
&\tau_{m,k} = \exp(\gamma_{m,k}) + \tau_{k-1}, \ k = 2, \ldots, K_m - 1, m \text{ ordered}
\end{aligned}$$

and estimate the $(\delta_{m,m}, \xi_{m,n}, \gamma_k)$ instead of the original parameters. The parameter values are estimated using the *cmp* package in Stata (Roodman, 2011). Table 8 gives parameter estimates for the indices while Table 9 gives parameter estimates of the covariance matrix in the outcomes.

4.2 Trends for replenishing cohorts

Using the jointly estimated models previously described, we then assign outcomes to the replenishing cohorts, imposing trends for some health, risk factor, and social outcomes. We currently impose trends on BMI, education, number of children, marital status, hypertension, and smoking status for these 25-26 year olds. These trends are estimated using the National Health Interview Survey (health and risk factors) or the American Community Survey (social outcomes). All trends are halted after 2029. The trends are shown in Table 10, Table 11 and Table 12.

5 Implementation

The FAM is implemented in multiple parts. Estimation of the transition and cross sectional models is performed in Stata. The replenishing cohort model is estimated in Stata using the CMP package (Roodman, 2011). The simulation is implemented in C++ for speed and flexibility. Currently, the simulation is run on Linux, Windows, and Mac OS X.

To match the two year structure of the PSID data used to estimate the transition models, the FAM simulation proceeds in two year increments. The end of each two year step is designed to occur on July 1st to allow for easier matching to population forecasts from Social Security. A simulation of the FAM proceeds by first loading a population representative of the age 25+ US population in 2009, generated from PSID. In two year increments, the FAM applies the transition models for mortality, health, working, wealth, earnings, and benefit claiming with Monte Carlo decisions to calculate the new states of the population. Once the simulation begins, trends in mortality are applied. Separate mortality rate adjustment factors are defined for the under and over 65 age groups based on the mortality projections from the 2013 SSA Trustees report. The SSA projections are interpolated through 2090, then extended using GLM with log link through 2150. The average yearly all-cause mortality reduction between 2020 and 2150 was 1.06% for ages 25-64, and 0.66% for the 65+ population. The population is also adjusted by immigration forecasts from the US Census Department, stratified by race and age. If incoming cohorts are being used, the new 25/26 year olds are added to the population. The number of new 25/26 year olds added is consistent with estimates from the Census, stratified by race. Once the new states have been determined and new 25/26 year olds added, the cross sectional models for medical costs are performed. Summary variables are then computed. Computation of medical costs includes the persons that died to account for end of life costs. To reduce uncertainty due to the Monte Carlo decision rules, the simulation is performed multiple times (here 75), and the mean of each summary variable is calculated across repetitions.

FAM simulation takes as inputs assumptions regarding the normal retirement age, real medical cost growth, and interest rates. The default assumptions are taken from the 2010 Social Security Intermediate scenario, adjusted for no price increases after 2010. Therefore simulation results are in real 2009 dollars.

Different simulation scenarios are implemented by changing any of the following components: incoming cohort model, transition models, interventions that adjust the probabilities of specific transition, and changes to assumptions on future economic conditions.

6 Validation

We perform cross-validation and external corroboration exercises. Cross-validation is a test of the simulation's internal validity that compares simulated outcomes to actual outcomes. External corroboration compares model forecasts to others' forecasts.

6.1 Cross-validation

The cross-validation exercise randomly samples half of the PSID respondent IDs for use in estimating the transition models. The respondents not used for estimation, but who were present in the PSID sample in 1999, are then simulated from 1999 through 2019. Demographic, health, and economic outcomes are compared between the simulated ("FAM") and actual ("PSID") populations.

Worth noting is how the composition of the population changes in this exercise. In 1999, the sample represents those 25 and older. Since we follow a fixed cohort, the age of the population will increase to 45 and older in 2019. This has consequences for some measures in later years where the eligible population shrinks.

6.1.1 Demographics

Mortality and demographic measures are presented in Tables 13 and 14. Mortality incidence is comparable between the simulated and observed populations. Demographic characteristics do not differ between the two.

6.1.2 Health Outcomes

Binary health outcomes are presented in Table 15. FAM underestimates the prevalence of ADL and IADL limitations compared to the crossvalidation sample. Binary outcomes, like cancer, diabetes, and hypertension do not differ. FAM underpredicts stroke, and heart and lung disease compared to the crossvalidation sample.

6.1.3 Health Risk Factors

Risk factors are presented in Table 16. BMI is not statistically different between the two samples. Current smoking is not statistically different, but more individuals in the crossvalidation sample report being former smokers.

On the whole, the crossvalidation exercise is reassuring. There are differences that will be explored and improved upon in the future.

6.2 External Corroboration

Finally, we compare FAM population forecasts to Census forecasts of the US population. Here, we focus on the full PSID population (25 and older) and those 65 and older. For this exercise, we begin the simulation in 2009 and simulate the full population through 2049. Population projections are compared to the 2012 Census projections for years 2012 through 2049. See results in Table 17. By 2049, FAM forecasts for 25 and older remain within 3% of Census forecasts.

7 Baseline Forecasts

In this section we present baseline forecasts of the Future Adult Model. The figures show data from the PSID for the 25+ population from 1999 through 2009 and forecasts from the FAM for the 25+ population beginning in 2009.

7.1 Disease Prevalence

Figure 2 depicts the six chronic conditions we project for men. And Figure 3 depicts the historic and forecasted values for women.

Figure 4 shows historic and forecasted levels for any ADL difficulties, three or more ADL difficulties, any IADL difficulties, and two or more IADL difficulties for men 25 and older. Figure 5 shows historic and forecasted levels for any ADL difficulties, three or more ADL difficulties, any IADL difficulties, and two or more IADL difficulties for women 25 and older.

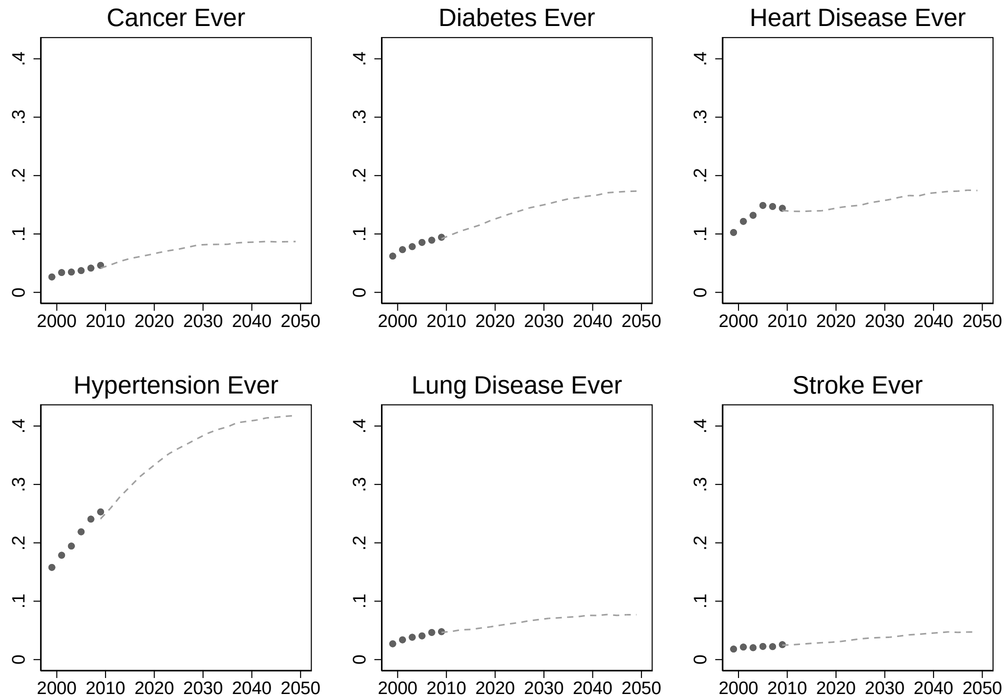

Figure 2: Historic and Forecasted Chronic Disease Prevalence for Men 25+

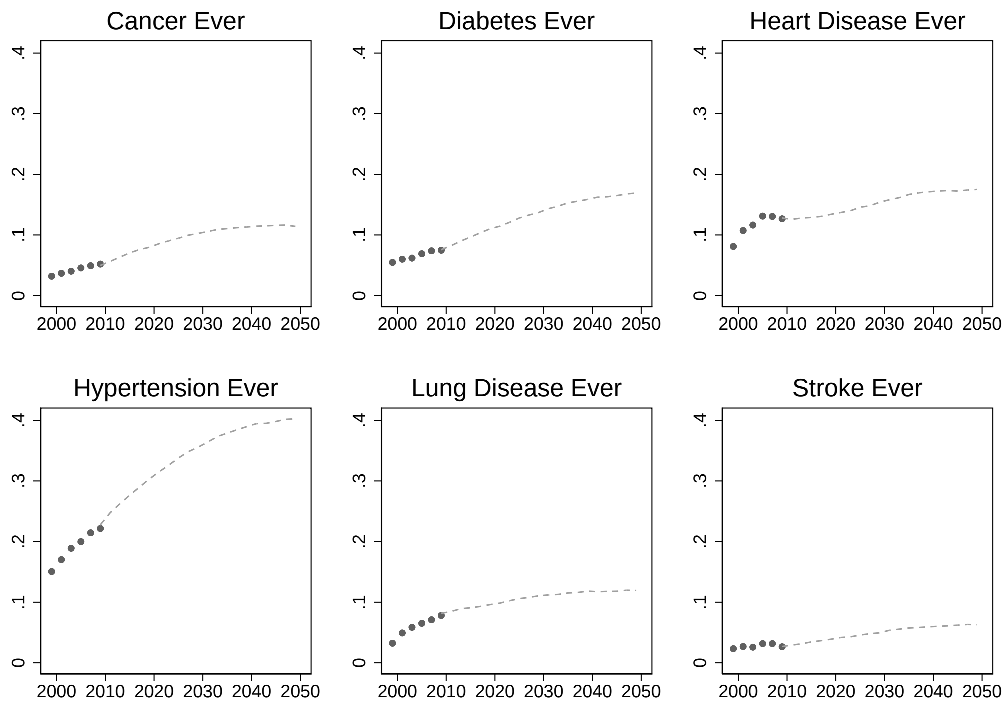

Figure 3: Historic and Forecasted Chronic Disease Prevalence for Women 25+

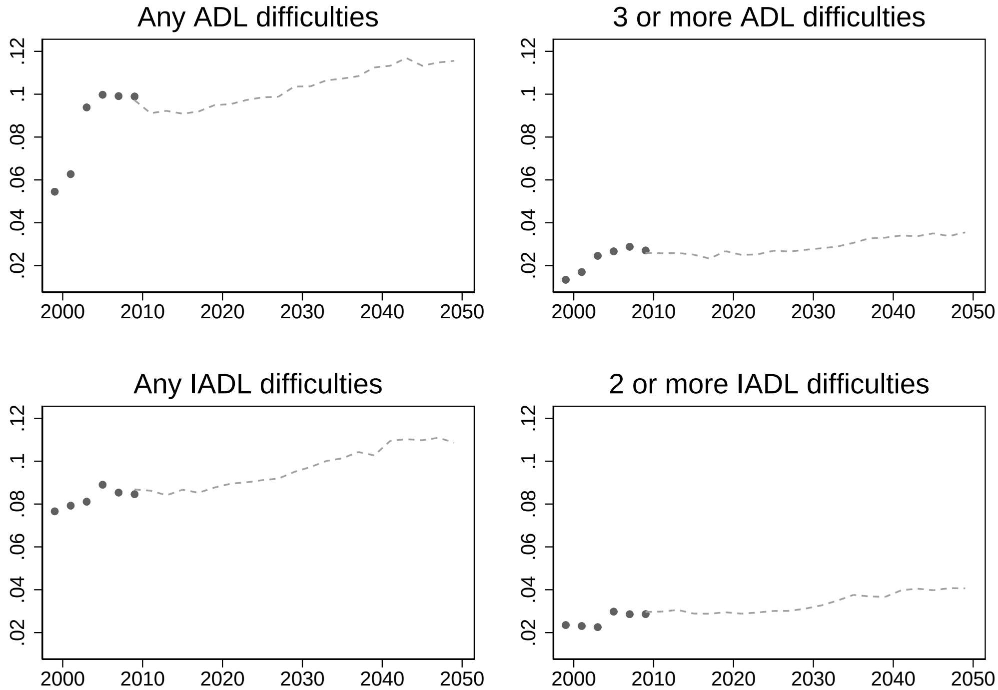

Figure 4: Historic and Forecasted ADL and IADL Prevalence for Men 25+

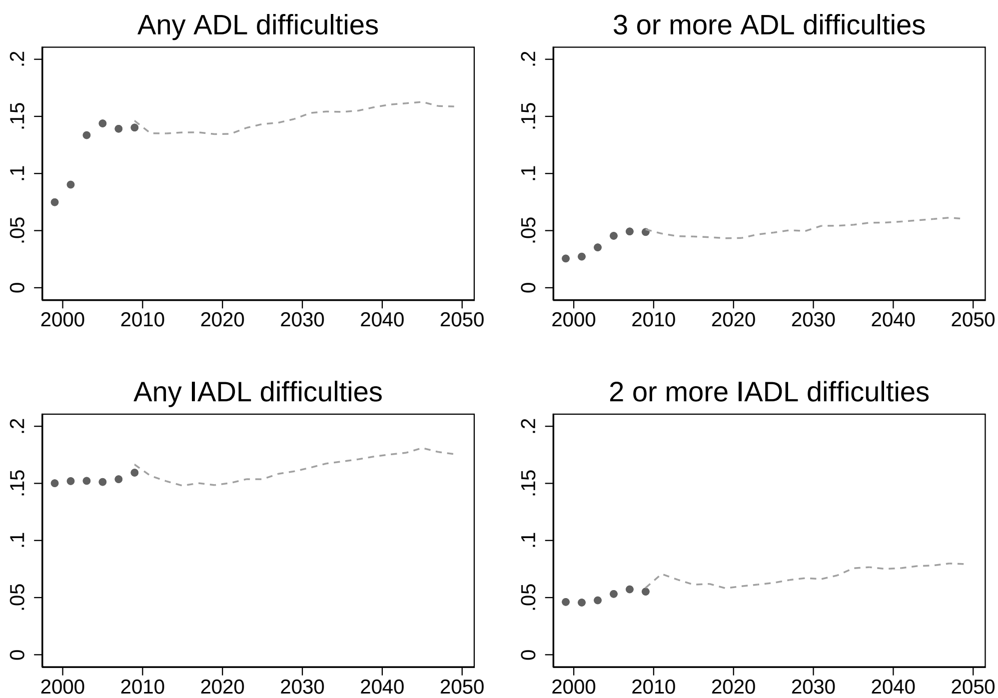

Figure 5: Historic and Forecasted ADL and IADL Prevalence for Women 25+

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9 Tables

Economic Outcomes	**Health Outcomes**	**Other Outcomes**
Work Status	BMI Category	Education
Earnings	Smoking Category	Partnered
Wealth	Hypertension	Partner Type
		Health Insurance

Table 1: Estimated outcomes in replenishing cohorts module

Economic Outcomes	Health Outcomes	Marital Status	Other Outcomes
Social Security Claiming	Mortality	Exit Single	Insurance Type
Disability Claiming	Heart Disease	Exit Cohabitation	
Non-Zero Capital Income	Cancer	Exit Married	
Capital Income (if non-zero)	Hypertension	Single to Married	
Non-zero Government Transfers	Diabetes	Cohabitation to Married	
Government Transfers (if non-zero)	Lung Disease	Married to Cohabitation	
Non-zero Wealth	Start Smoking		
Wealth (if non-zero)	Stop Smoking		
Labor Force Status (out, unemployed, working)	ADL Status		
Employed Full- or Part-time (if working)	IADL Status		
Any Earnings (if Unemployed)	Births/Paternity		
Any Earnings (if Not in Labor Force)	Self-reported Health		
Earnings (if Full-time)	BMI		
Earnings (if Part-time)	Partner Death		
Earnings (if Unemployed and any)			
Earnings (if Not in Labor Force and any)			

Table 2: Estimated outcomes in transitions module

	Prevalence %							
Source (years, ages)	Cancer	Heart Diseases	Stroke	Diabetes	Hypertension	Lung Disease	Overweight	Obese
HRS (2004-2008, 50-64)	9%	14%	4%	18%	45%	7%	37%	38%
HRS (2004-2008, 65+)	20%	31%	11%	24%	64%	11%	38%	29%
MCBS (2007-2010, 65+)	19%	41%	11%	25%	68%	17%	38%	26%
MEPS (2007-2010, 25-49)	2%	6%	1%	4%	18%	4%	35%	30%
MEPS (2007-2010, 50-64)	6%	16%	4%	14%	46%	7%	37%	34%
MEPS (2007-2010, 65+)	14%	36%	12%	21%	68%	11%	38%	27%
NHIS (2007-2009, 25-49)	2%	6%	1%	4%	16%	4%	34%	31%
NHIS (2007-2009, 50-64)	7%	14%	3%	13%	41%	7%	36%	35%
NHIS (2007-2009, 65+)	17%	32%	9%	19%	61%	10%	36%	27%
PSID (2007-2011, 25-49)	2%	4%	1%	4%	12%	3%	34%	29%
PSID (2007-2011, 50-64)	6%	14%	3%	13%	33%	8%	38%	30%
PSID (2007-2011, 65+)	16%	34%	8%	20%	53%	15%	38%	23%

Table 3: Health condition prevalences in survey data

	Survey			
Disease	PSID/HRS	NHIS	MEPS	MCBS
Cancer	Has a doctor ever told you that you have cancer or a malignant tumor, excluding minor skin cancers?	Have you ever been told be a doctor or other health professional that you had cancer or a malignanacy of any kind? (WHEN RECODED, SKIN CANCERS WERE EXCLUDED)	List all the conditions that have bothered (the person) from (START time) to (END time) CCS codes for the conditions list are 11-21, 24-45	Has a doctor ever told you that you had any (other) kind of cancer malignancy, or tumor other than skin cancer?
Heart Diseases	Has a doctor ever told you that you had a heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems?	Four separate questions were asked about whether ever told by a docotor or oither health professional that had: CHD, Angina, MI, other heart problems.	Have you ever been told by a doctor or health professional that you have CHD; Angina; MI; other heart problems	Six separate questions were asked about whether ever told by a doctor that had: Angina or MI; CHD; other heart problems (included four questions)
Stroke	Has a doctor ever told you that you had a stroke?	Have you EVER been told by a doctor or other health professional that you had a stroke?	If Female, add: [Other than during pregnancy,] Have you ever been told by a doctor or health professional that you have a stroke or TIA (transient ischemic attack)	[Since (PREV< SUPP. RD. INT. DATE),] has a doctor (ever) told (you/SP) that (you/he/she) had a stroke, a brain hemorrhage, or a cerebrovascular accident?
Diabetes	Has a doctor ever told you that you have diabetes or high blood sugar?	If Female, add: [Other than during pregnancy,] Have you ever been told by a doctor or health professional that you have diabetes or sugar diabetes?	If Female, add: [Other than during pregnancy,] Have you hever been told by a doctor or health professional that you have diabetes or sugar diabetes?	Has a doctor (ever) told (you/SP) that (you/he/she) had diabetes, high blood sugar, or sugar in (your/his/her) urine? [DO NOT INCLUDE BOERDERLINE PREGNANCY, OR PREDIABETEIC DIABETES.]
Hypertension	Has a doctor ver told you that you have high blood pressure or hypertension?	Have you EVER been told by a doctor or other health professional that you had Hypertension, also called high blood pressure?	Have you EVER been told by a doctor or other health professional that you had Hypertension, also called high blood pressure?	Has a doctor (ever) told (you/SP) that (you/he/she) (still) (had) (have/has) hypertension, sometimes called high blood pressure?
Lung Disease	Has a doctor ever told you that you have chronic lung disease such a schronic bronchitis or emphysema? [IWER: DO NOT INCLUDE ASTHMA]	Question 1: During the PAST 12 MONTHS, have you ever been told by a doctor or other health professional that you had chronic bronchitis? Question 2: Have you EVER been told by a docotor or other health professional that you had emphysema?	List all the conditions that have bothered (the person) from (START time) to (END time) CCS codes for the conditions list are 127, 129-312	Has a doctor (ever) told (you/SP) that (you/he/she) had emphysema, asthma, or COPD? [COPD=CHRONIC OBSTRUCTIVE PULMONARY DISEASE.]
Overweight	Self-reported body weight and height			
Obese				

Table 4: Survey questions used to determine health conditions

			Type	At risk	Mean/fraction
Disease	heart disease		biennial incidence	undiagnosed	0.01
	hypertension		biennial incidence	undiagnosed	0.04
	stroke		biennial incidence	undiagnosed	0.01
	lung disease		biennial incidence	undiagnosed	0.01
	cancer		biennial incidence	undiagnosed	0.01
	diabetes		biennial incidence	undiagnosed	0.01
Risk Factors	Smoking Status	never smoked	ordered	all	0.51
		ex smoker	ordered	all	0.30
		current smoker	ordered	all	0.19
	Log BMI		continuous	all	3.31
	ADL Status	no ADLs	ordered	all	0.90
		1 ADL	ordered	all	0.05
		2 ADLS	ordered	all	0.02
		3+ ADLS	ordered	all	0.03
	IADL Status	no IADLs	ordered	all	0.89
		1 IADL	ordered	all	0.07
		2+ IADLs	ordered	all	0.04
LFP & Benefits	Employment Status	out of labor force	prevalence	all	0.26
		unemployed	prevalence	all	0.06
		part time	prevalence	all	0.17
		full time	prevalence	all	0.51
	SS benefit receipt		biennial incidence	eligible & not receiving	
	DI benefit receipt		prevalence	eligible & age < 65	0.04
	Any health insurance		prevalence	age < 65	0.84
	SSI receipt		prevalence	all	0.02
Family	Marital status	single	prevalence	all	0.28
		cohabitating	prevalence	all	0.09
		married	prevalence	all	0.62
	Childbearing	no children	biennial incidence	female	0.91
		1 child	biennial incidence	female	0.08
		2 children	biennial incidence	female	0.00
Financial Resources ($K 2009)	financial wealth		median	all non-zero wealth	56.00
	earnings		median	working full time	17.50
	earnings		median	working part time	40.38
	wealth non-zero		prevalence	all	0.95

Table 5: Outcomes in the transition model. Estimation sample is PSID 1999-2019 waves.

Value at time $T-1$	Outcome at time T																			
	Heart disease	hypertension	stroke	Lung disease	diabetes	cancer	disability	mortality	Smoking status	BMI	Any HI	DI Claim	SS Claim	DB Claim	SSI Claim	Nursing Home	Work	Earnings	Nonzero Wealth	Wealth
Heart disease			✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Blood pressure	✓		✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Stroke							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lung disease							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Diabetes	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cancer			✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Disability							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Claimed DI											✓	✓	✓	✓	✓		✓	✓	✓	✓
Claimed SS											✓			✓	✓		✓	✓	✓	✓
Claimed DB													✓		✓		✓	✓	✓	✓
Claimed SSI															✓					
Work											✓	✓	✓		✓		✓	✓	✓	✓
Earnings											✓	✓	✓	✓	✓		✓	✓	✓	✓
Nonzero wealth											✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wealth											✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nursing home stay															✓	✓			✓	✓

Table 6: Restrictions on transition model. ✓indicates that an outcome at time $T-1$ is allowed in the transition model for an outcome at time T.

Control variable	Mean	Standard deviation	Minimum	Maximum
Non-hispanic black	0.112	0.315	0	1
Hispanic	0.127	0.333	0	1
Single	0.343	0.475	0	1
Cohabitating	0.0540	0.226	0	1
Married	0.603	0.489	0	1
Less than high school	0.133	0.340	0	1
High school/GED/some college/AA	0.552	0.497	0	1
College graduate	0.210	0.407	0	1
More than college	0.105	0.307	0	1
Doctor ever - heart disease	0.140	0.347	0	1
Doctor ever - hypertension	0.242	0.428	0	1
Doctor ever - stroke	0.0286	0.167	0	1
Doctor ever - chronic lung disease	0.0677	0.251	0	1
Doctor ever - cancer	0.0492	0.216	0	1
Doctor ever - diabetes	0.0871	0.282	0	1
Never smoked	0.473	0.499	0	1
Former smoker	0.346	0.476	0	1
Current smoker	0.181	0.385	0	1
No ADL limitations	0.869	0.337	0	1
1 ADL limitation	0.0595	0.237	0	1
2 ADL limitations	0.0262	0.160	0	1
3 or more ADL limitations	0.0454	0.208	0	1
No IADL limitations	0.866	0.340	0	1
1 IADL limitation	0.0858	0.280	0	1
2 or more IADL limitations	0.0479	0.214	0	1
$25 < \text{BMI} < 30$	0.366	0.482	0	1
$30 < \text{BMI} < 35$	0.168	0.374	0	1
$35 < \text{BMI} < 40$	0.0662	0.249	0	1
$\text{BMI} > 40$	0.0382	0.192	0	1
Any Social Security income LCY	0.199	0.399	0	1
Any Disability income LCY	0.0388	0.193	0	1
Any Supplemental Security Income LCY	0.0188	0.136	0	1
Any health insurance LCY	0.876	0.329	0	1
Out of labor force	0.317	0.465	0	1
Unemployed	0.0620	0.241	0	1
Working part-time	0.177	0.382	0	1
Working full-time	0.444	0.497	0	1
Earnings in 1000s capped at 200K	34.01	39.98	0	200
Wealth in 1000s capped at 2 million	269.4	457.1	-1974	2000

Table 7: Desciptive statistics for variables in 2009 PSID ages 25+ sample used as simulation stock population

Covariate	Education level	Partnered	Partnership type	Weight status	Smoking status	Hypertension	In labor force	Number of biological children
Non-hispanic black	-0.31	-0.69	-0.60	0.37	-0.38	0.21	0.17	0.35
Hispanic	-0.04	0.02	-0.16	0.27	-0.51	-0.09	-0.06	0.22
Male	-0.26	0.06	-0.17	0.13	0.25	0.13	0.49	-0.40
Less than HS/GED	0.00	-0.39	0.33	0.02	0.75	0.03	-0.37	0.19
College	0.00	0.13	-0.30	-0.43	-0.72	-0.10	0.34	-0.54
Beyond college	0.00	0.32	-0.70	-0.78	-1.03	-0.21	0.05	-0.62
R’s mother less than high school	-0.32	-0.09	-0.09	0.00	0.00	0.00	-0.04	0.18
R;s mother some college	0.32	-0.17	0.17	0.00	0.00	0.00	-0.11	-0.12
R’s mother college graduate	0.59	-0.28	0.09	0.00	0.00	0.00	-0.00	-0.25
R’s father less than high school	-0.15	-0.04	0.05	0.00	0.00	0.00	-0.02	-0.02
R;s father some college	0.29	-0.22	0.16	0.00	0.00	0.00	-0.00	-0.25
R’s father college graduate	0.70	-0.27	0.18	0.00	0.00	0.00	-0.06	-0.37
Poor as a child	-0.21	0.04	-0.05	0.00	0.00	0.00	-0.08	0.12
Wealthy as a child	-0.06	-0.05	-0.05	0.00	0.00	0.00	-0.05	0.11
Fair or poor health before age 17	-0.17	-0.10	-0.06	0.00	0.00	0.00	-0.19	-0.03
Age 25 or 26	-0.14	-0.19	-0.25	-0.11	-0.02	-0.15	-0.06	-0.30
Constant	1.45	0.94	0.81	0.15	0.10	-1.84	0.97	0.57

Table 8: Parameter estimates for latent model: conditional means and thresholds. Sample is respondents age 25-30 in 2005-2011 PSID waves

	Education level	Partnered	Partnership type	Weight status	Smoking status	Hypertension	In labor force	Number of biological children
Education level	1.000							
Partnered	-0.139	1.000						
Partnership type	0.351	0.000	1.000					
Weight status	0.139	-0.019	0.100	1.000				
Smoking status	0.004	-0.122	-0.192	-0.022	1.000			
Hypertension	-0.025	-0.074	0.056	0.320	0.021	1.000		
In labor force	-0.022	-0.146	-0.037	-0.022	-0.008	-0.003	1.000	
Number of biological children	-0.168	0.352	0.207	0.006	0.002	0.023	-0.181	1.000

Table 9: Parameter estimates for latent model: parameterized covariance matrix. Sample is respondents age 25-30 in 2005-2011 PSID waves

Year	Hypertension	Overweight	Obese 1	Obese 2	Obese 3	Never Smoked	Former Smoker	Current Smoker
2009	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2010	1.00	1.00	1.03	1.01	1.01	1.00	1.00	0.99
2011	0.99	1.00	1.06	1.01	1.03	1.01	0.99	0.98
2012	0.99	1.00	1.08	1.01	1.04	1.01	0.99	0.98
2013	1.00	1.00	1.10	1.02	1.06	1.01	0.99	0.97
2014	1.00	1.01	1.12	1.02	1.07	1.02	0.98	0.96
2015	1.00	1.00	1.14	1.03	1.08	1.02	0.98	0.95
2016	1.01	1.02	1.17	1.03	1.10	1.03	0.98	0.94
2017	1.01	1.03	1.19	1.04	1.11	1.03	0.97	0.94
2018	0.98	1.09	1.20	1.05	1.13	1.03	0.97	0.93
2019	0.98	1.09	1.23	1.06	1.14	1.04	0.97	0.92
2020	0.99	1.09	1.24	1.08	1.16	1.04	0.96	0.91
2021	0.99	1.09	1.26	1.09	1.17	1.04	0.96	0.91
2022	0.98	1.09	1.28	1.11	1.19	1.05	0.95	0.90
2023	0.98	1.09	1.29	1.13	1.20	1.05	0.95	0.89
2024	0.98	1.08	1.30	1.15	1.22	1.05	0.95	0.88
2025	0.98	1.07	1.31	1.18	1.24	1.06	0.94	0.87
2026	0.99	1.06	1.32	1.21	1.25	1.06	0.94	0.87
2027	0.99	1.04	1.34	1.24	1.27	1.06	0.94	0.86
2028	0.99	0.98	1.43	1.25	1.28	1.07	0.93	0.85
2029	1.01	0.97	1.46	1.26	1.30	1.07	0.93	0.84
2030	1.01	0.97	1.46	1.26	1.30	1.07	0.93	0.84
2031	1.01	0.97	1.46	1.26	1.30	1.07	0.93	0.84
2032	1.01	0.97	1.46	1.26	1.30	1.07	0.93	0.84
2033	1.01	0.97	1.46	1.26	1.30	1.07	0.93	0.84
2034	1.01	0.97	1.46	1.26	1.30	1.07	0.93	0.84
2035	1.01	0.97	1.46	1.26	1.30	1.07	0.93	0.84

Table 10: Health and risk factor trends for replenishing cohorts, prevalences relative to 2009

Year	Less than HS	HS Grad	College Grad	Graduate School
2009	1.00	1.00	1.00	1.00
2010	0.98	0.99	1.02	1.04
2011	0.96	0.99	1.04	1.08
2012	0.95	0.98	1.05	1.12
2013	0.93	0.97	1.07	1.16
2014	0.91	0.96	1.09	1.20
2015	0.89	0.96	1.11	1.25
2016	0.87	0.95	1.13	1.29
2017	0.86	0.94	1.14	1.34
2018	0.84	0.93	1.16	1.39
2019	0.82	0.93	1.18	1.44
2020	0.81	0.92	1.20	1.49
2021	0.79	0.91	1.21	1.54
2022	0.77	0.90	1.23	1.59
2023	0.76	0.89	1.25	1.65
2024	0.74	0.88	1.27	1.70
2025	0.73	0.87	1.28	1.76
2026	0.71	0.87	1.30	1.82
2027	0.69	0.86	1.32	1.88
2028	0.68	0.85	1.33	1.94
2029	0.66	0.84	1.35	2.00
2030	0.66	0.84	1.35	2.00
2031	0.66	0.84	1.35	2.00
2032	0.66	0.84	1.35	2.00
2033	0.66	0.84	1.35	2.00
2034	0.66	0.84	1.35	2.00
2035	0.66	0.84	1.35	2.00

Table 11: Education trends for replenishing cohorts, prevalences relative to 2009

Year	No Children	One Child	Two Children	Three Chidren	Four or More Children	Partnered	Married
2009	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2010	1.01	1.00	0.99	0.98	0.98	1.00	0.98
2011	1.01	0.99	0.98	0.97	0.95	0.99	0.96
2012	1.02	0.99	0.97	0.95	0.93	0.99	0.94
2013	1.03	0.98	0.96	0.93	0.90	0.99	0.91
2014	1.03	0.98	0.95	0.91	0.88	0.99	0.89
2015	1.04	0.97	0.94	0.90	0.86	0.98	0.87
2016	1.05	0.97	0.92	0.88	0.84	0.98	0.85
2017	1.05	0.96	0.91	0.87	0.82	0.98	0.82
2018	1.06	0.95	0.90	0.85	0.79	0.98	0.80
2019	1.07	0.95	0.89	0.83	0.77	0.98	0.78
2020	1.07	0.94	0.88	0.82	0.75	0.98	0.76
2021	1.08	0.94	0.87	0.80	0.73	0.98	0.73
2022	1.09	0.93	0.86	0.79	0.72	0.97	0.71
2023	1.09	0.93	0.85	0.77	0.70	0.97	0.69
2024	1.10	0.92	0.84	0.76	0.68	0.97	0.66
2025	1.11	0.92	0.83	0.75	0.66	0.97	0.64
2026	1.11	0.91	0.82	0.73	0.64	0.98	0.62
2027	1.12	0.90	0.81	0.72	0.63	0.98	0.60
2028	1.13	0.90	0.80	0.70	0.61	0.98	0.57
2029	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2030	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2031	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2032	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2033	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2034	1.13	0.89	0.79	0.69	0.59	0.98	0.55
2035	1.13	0.89	0.79	0.69	0.59	0.98	0.55

Table 12: Social trends for replenishing cohorts, prevalences relative to 2009

	2001			2007			2013			2019		
	FAM	PSID		FAM	PSID		FAM	PSID		FAM	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p	mean	mean	p
Died	0.016	0.018	0.173	0.020	0.023	0.233	0.026	0.026	0.834	0.031	0.032	0.865

Table 13: Crossvalidation of 1999 cohort: Mortality in 2001, 2007, 2013, and 2019

	2001			2007			2013			2019		
	FAM	PSID		FAM	PSID		FAM	PSID		FAM	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p	mean	mean	p
Age on July 1st	48.865	49.331	0.043	53.037	53.486	0.049	56.891	58.078	0.000	60.806	62.800	0.000
Black	0.102	0.090	0.004	0.102	0.088	0.001	0.101	0.092	0.051	0.101	0.094	0.201
Hispanic	0.075	0.072	0.320	0.080	0.086	0.228	0.088	0.096	0.109	0.094	0.091	0.689
Male	0.465	0.467	0.732	0.463	0.463	0.938	0.460	0.458	0.778	0.456	0.459	0.744

Table 14: Crossvalidation of 1999 cohort: Demographic outcomes in 2001, 2007, 2013, and 2019

	2001			2007			2013			2019		
	FAM	PSID		FAM	PSID		FAM	PSID		FAM	PSID	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p	mean	mean	p
Any ADLs	0.080	0.070	0.009	0.107	0.126	0.000	0.128	0.142	0.019	0.151	0.204	0.000
Any IADLs	0.099	0.115	0.001	0.112	0.130	0.001	0.133	0.170	0.000	0.153	0.210	0.000
Cancer	0.036	0.036	0.996	0.062	0.052	0.004	0.089	0.073	0.000	0.119	0.125	0.297
Diabetes	0.065	0.062	0.321	0.096	0.088	0.077	0.132	0.122	0.084	0.174	0.176	0.726
Heart Disease	0.096	0.110	0.003	0.128	0.152	0.000	0.156	0.173	0.009	0.193	0.214	0.006
Hypertension	0.175	0.168	0.152	0.265	0.252	0.045	0.356	0.329	0.001	0.443	0.458	0.112
Lung Disease	0.036	0.038	0.532	0.060	0.058	0.535	0.083	0.091	0.088	0.103	0.124	0.001
Stroke	0.019	0.021	0.175	0.027	0.031	0.165	0.037	0.035	0.556	0.047	0.057	0.022

Table 15: Crossvalidation of 1999 cohort: Binary health outcomes in 2001, 2007, 2013, and 2019

	2001			2007			2013			2019		
Outcome	FAM mean	PSID mean	p	FAM mean	PSID mean	p	FAM mean	PSID mean	p	FAM mean	PSID mean	p
BMI	26.796	26.724	0.338	27.544	27.454	0.313	28.049	27.759	0.004	28.338	27.968	0.002
Current smoker	0.183	0.201	0.002	0.155	0.167	0.047	0.132	0.146	0.015	0.110	0.119	0.116
Ever smoked	0.471	0.511	0.000	0.468	0.525	0.000	0.461	0.531	0.000	0.451	0.532	0.000

Table 16: Crossvalidation of 1999 cohort: Risk factor outcomes in 2001, 2007, 2013, and 2019

Year	Census 25+	FAM Minimal 25+	Census 65+	FAM Minimal 65+
2009	202.1	202.0	39.6	39.4
2011	206.6	205.3	41.4	39.7
2013	211.0	209.2	44.7	42.6
2015	215.9	213.9	47.7	45.8
2017	220.9	218.5	50.8	48.6
2019	225.5	223.2	54.2	51.3
2021	229.8	227.2	57.7	54.5
2023	233.9	230.8	61.4	57.0
2025	238.0	234.6	65.1	60.5
2027	241.9	238.2	68.4	63.9
2029	245.7	241.7	71.4	67.2
2031	249.3	245.2	73.8	69.9
2033	252.9	248.5	75.5	71.1
2035	256.0	251.5	77.3	73.5
2037	259.2	254.4	78.8	73.9
2039	262.6	257.2	79.4	74.2
2041	265.8	260.2	79.9	74.0
2043	269.0	262.5	80.4	74.5
2045	272.2	265.2	81.3	75.4
2047	275.3	268.0	82.2	76.2
2049	278.4	270.7	83.2	76.5

Table 17: Population forecasts: Census compared to FAM

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This file provides supplementary details for the paper:
Title: The Effect of US COVID-19 Excess Mortality on Social Security Outlays
Authors: Hanke Heun-Johnson, Darius Lakdawalla, Julian Reif, and Bryan Tysinger

The following sheets contain transition model estimates for relevant variables in the Future Adult Model, for the population ages 25-54 years in 2020.

Binaries - health
This worksheet reports estimates of the probability of developing a chronic condition (stroke, heart disease, cancer, hypertension, diabetes, and lung disease), of exercise status, of initiating smoking, and of ceasing smoking.

Binaries - econ
This worksheet reports estimates of the probability of claiming OASI and DI, and working

Binaries - relationship
This worksheet reports estimates of the probability of transitioning between types of relationships

Ordered probits
This worksheet reports estimates of the probability of changing ADL and IADL status, as well as the number of new children

OLS
This worksheet reports estimates of how BMI is updated in the microsimulation, and estimates of OASDI benefit amounts

multlogit
This worksheet reports estimates of labor force status

Mortality & nursing home
This worksheet reports estimates of the probability of dying, of one's partner dying, and of living in nursing home (ages 55+ only).
These models are estimated on a combined sample of PSID and HRS respondents.

Binaries - health

	Stroke (stroke) coefficients		Stroke (stroke) marginal effects		Heart disease (hearte) coefficients		Heart disease (hearte) marginal effects		Any exercise (anyexercise) coefficients		Any exercise (anyexercise) marginal effects		Cancer (cancre) coefficients		Cancer (cancre) marginal effects	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-hispanic black	0.140***	0.047	0.001		-0.018	0.038	-0.000		-0.346***	0.017	-0.076		-0.217***	0.045	-0.003	
Hispanic	0.028	0.087	0.000		-0.170**	0.083	-0.004		-0.216***	0.030	-0.048		-0.417***	0.114	-0.005	
Less than HS/GED	0.137***	0.040	0.001		0.180***	0.042	0.006		-0.310***	0.022	-0.071		-0.042	0.050	-0.001	
College	-0.166***	0.052	-0.001		-0.096***	0.037	-0.002		0.334***	0.019	0.060		0.077**	0.035	0.001	
Beyond college	-0.206***	0.076	-0.001		-0.067	0.049	-0.002		0.415***	0.028	0.068		0.023	0.047	0.000	
Male	-0.584	1.003	-0.005		-0.201	0.529	-0.005		0.066***	0.024	0.013		-1.580	1.043	-0.035	
Black male	0.064	0.069	0.001		-0.053	0.050	-0.001		0.033	0.023	0.006		0.039	0.064	0.001	
Hispanic male	-0.405**	0.165	-0.002		-0.046	0.091	-0.001		-0.044	0.035	-0.009		0.050	0.120	0.001	
Poor as a child	-0.019	0.036	-0.000		0.040	0.025	0.001		-0.003	0.012	-0.001		0.064**	0.027	0.001	
Wealthy as a child	0.069	0.046	0.001		0.027	0.031	0.001		-0.068***	0.014	-0.014		0.005	0.036	0.000	
Childhood health - fair	0.017	0.139	0.000		-0.158	0.099	-0.004		0.124**	0.051	0.023		0.069	0.130	0.001	
Childhood health - good	-0.100	0.124	-0.001		-0.231***	0.086	-0.005		0.131***	0.045	0.025		-0.010	0.117	-0.000	
Childhood health - very good	-0.156	0.122	-0.001		-0.355***	0.085	-0.008		0.227***	0.044	0.043		-0.015	0.115	-0.000	
Childhood health - excellent	-0.148	0.120	-0.001		-0.346***	0.083	-0.010		0.253***	0.043	0.052		0.008	0.113	0.000	
Age spline, less than 35	-0.000	0.019	-0.000		0.009	0.011	0.000		-0.006*	0.003	-0.001		0.012	0.014	0.000	
Age spline, 35 to 44	0.034***	0.013	0.000		0.025***	0.008	0.001		-0.017***	0.002	-0.003		0.027***	0.009	0.000	
Age spline, 45 to 54	-0.001	0.010	-0.000		-0.000	0.007	-0.000		-0.012***	0.002	-0.002		0.025***	0.007	0.000	
Age spline, 55 to 64	0.025**	0.010	0.000		0.015**	0.007	0.000		-0.011***	0.003	-0.002		0.013*	0.007	0.000	
Age spline, 65 to 74	0.006	0.010	0.000		0.024***	0.008	0.001		-0.015***	0.003	-0.003		0.020**	0.008	0.000	
Age spline, more than 75	0.031***	0.007	0.000		0.034***	0.007	0.001		-0.034***	0.003	-0.007		0.003	0.007	0.000	
Male, age spline less than 35	0.016	0.033	0.000		0.006	0.018	0.000						0.038	0.034	0.001	
Male, age spline 35 to 44	-0.005	0.020	-0.000		-0.001	0.011	-0.000						0.000	0.017	0.000	
Male, age spline 45 to 54	0.017	0.015	0.000		0.028***	0.010	0.001						0.022*	0.012	0.000	
Male, age spline 55 to 64	0.001	0.014	0.000		-0.005	0.010	-0.000						0.018*	0.010	0.000	
Male, age spline 65 to 74	0.005	0.015	0.000		-0.004	0.012	-0.000						-0.001	0.011	-0.000	
Male, age spline over 75	-0.014	0.012	-0.000		-0.011	0.011	-0.000						0.013	0.010	0.000	
Lag of Doctor ever - heart disease	0.291***	0.038	0.003													
Lag of Doctor ever - cancer	0.124*	0.064	0.001													
Lag of Doctor ever - hypertension	0.318***	0.036	0.003		0.297***	0.025	0.010									
Lag of Doctor ever - diabetes	0.147***	0.044	0.001		0.170***	0.035	0.006									
Lag of Ever smoked cigarettes	0.084**	0.037	0.001		0.099***	0.026	0.003						0.013	0.028	0.000	
Lag of Current smoker	0.178***	0.044	0.002		0.177***	0.031	0.005						0.146***	0.036	0.003	
Lag of Any light or heavy physical activity	-0.161***	0.037	-0.001		-0.067**	0.029	-0.002		0.973***	0.012	0.273		0.016	0.034	0.000	
Log(BMI) spline, BMI < 30	-0.438***	0.133	-0.003		0.041	0.097	0.001						0.089	0.104	0.002	
Log(BMI) spline, BMI > 30	0.385**	0.151	0.003		0.854***	0.104	0.023						0.315**	0.130	0.005	
Black, Less than HS					-0.051	0.062	-0.001		0.105***	0.030	0.020		-0.012	0.082	-0.000	
Black, College					0.004	0.082	0.000		-0.026	0.036	-0.005		-0.083	0.098	-0.001	
Black, Beyond College					-0.213	0.144	-0.005		0.038	0.060	0.007		0.078	0.135	0.001	
Hispanic, Less than HS					-0.192*	0.105	-0.004		-0.017	0.040	-0.003		0.126	0.142	0.002	
Hispanic, College					0.201	0.151	0.007		-0.193***	0.062	-0.043		0.147	0.190	0.003	
Hispanic, Beyond College					0.301	0.188	0.012		0.068	0.099	0.013		0.327	0.219	0.008	
Lag of married from marriage history									0.098***	0.015	0.020					
Lag of cohab									0.012	0.028	0.002					
Male, previously married									0.019	0.025	0.004					
Male, previously cohabitating									0.036	0.041	0.007					
Lag of Doctor ever - chronic lung disease																
_cons	-1.554**	0.714			-2.753***	0.459			0.473***	0.105			-3.406***	0.541		

	Hypertension (hibpe) coefficients		Hypertension (hibpe) marginal effects		Diabetes (diabe) coefficients		Diabetes (diabe) marginal effects		Lung disease (lunge) coefficients		Lung disease (lunge) marginal effects		Start smoking (smoke_start) coefficients		Start smoking (smoke_start) marginal effects		Stop smoking (smoke_stop) coefficients		Stop smoking (smoke_stop) marginal effects	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-hispanic black	0.225***	0.027	0.020		-0.017	0.037	-0.000		0.027	0.040	0.001		0.136***	0.034	0.003		0.055	0.035	0.015	
Hispanic	0.101**	0.050	0.009		0.120*	0.067	0.003		-0.016	0.082	-0.000		-0.144**	0.064	-0.003		0.270***	0.078	0.079	
Less than HS/GED	0.052	0.035	0.004		0.142***	0.045	0.004		0.260***	0.043	0.006		0.208***	0.046	0.005		-0.223***	0.038	-0.056	
College	-0.024	0.025	-0.002		-0.067*	0.038	-0.002		-0.182***	0.045	-0.003		-0.331***	0.034	-0.006		0.329***	0.040	0.098	
Beyond college	-0.063*	0.036	-0.005		-0.061	0.052	-0.001		-0.287***	0.071	-0.004		-0.632***	0.068	-0.008		0.395***	0.084	0.122	
Male	0.435	0.323	0.038		-0.984*	0.590	-0.026		-0.216	0.508	-0.004		0.337	0.303	0.008		-0.288	0.302	-0.077	
Black male	-0.125***	0.035	-0.009		0.134***	0.049	0.004		0.050	0.055	0.001		0.126***	0.045	0.003		0.016	0.045	0.004	
Hispanic male	-0.156***	0.058	-0.011		0.078	0.075	0.002		-0.205*	0.109	-0.003		0.140*	0.074	0.004		0.017	0.091	0.005	
Poor as a child	0.044**	0.018	0.004		0.025	0.024	0.001		0.031	0.028	0.001		0.007	0.024	0.000		-0.026	0.024	-0.007	
Wealthy as a child	0.030	0.021	0.003		-0.016	0.031	-0.000		0.038	0.034	0.001		0.103***	0.026	0.002		0.083***	0.027	0.023	
Childhood health - fair	0.093	0.082	0.008		0.123	0.112	0.004		-0.060	0.104	-0.001		0.211*	0.115	0.006		0.039	0.116	0.010	
Childhood health - good	-0.008	0.073	-0.001		-0.021	0.101	-0.001		-0.231**	0.093	-0.004		0.134	0.105	0.003		-0.013	0.106	-0.004	
Childhood health - very good	-0.051	0.072	-0.004		0.007	0.100	0.000		-0.309***	0.091	-0.005		0.128	0.104	0.003		0.007	0.105	0.002	
Childhood health - excellent	-0.082	0.071	-0.007		-0.021	0.098	-0.001		-0.357***	0.090	-0.008		0.213**	0.103	0.004		0.049	0.104	0.013	
Age spline, less than 35	0.042***	0.008	0.003		0.005	0.011	0.000		-0.002	0.010	-0.000		-0.029***	0.007	-0.001		-0.019**	0.007	-0.005	
Age spline, 35 to 44	0.022***	0.005	0.002		0.024***	0.007	0.001		0.014*	0.008	0.000		-0.008	0.006	-0.000		-0.020***	0.006	-0.005	
Age spline, 45 to 54	0.023***	0.005	0.002		0.021***	0.006	0.001		0.022***	0.007	0.000		-0.026***	0.006	-0.001		0.022***	0.007	0.006	
Age spline, 55 to 64	0.017***	0.005	0.001		0.004	0.007	0.000		0.004	0.008	0.000		-0.037***	0.008	-0.001		0.005	0.009	0.001	
Age spline, 65 to 74	0.009	0.007	0.001		0.007	0.009	0.000		0.008	0.009	0.000		-0.018	0.013	-0.000		-0.009	0.015	-0.002	
Age spline, more than 75	0.010	0.006	0.001		0.003	0.008	0.000		0.003	0.008	0.000		-0.032*	0.017	-0.001		0.045*	0.024	0.012	
Male, age spline less than 35	-0.008	0.011	-0.001		0.024	0.019	0.001		0.002	0.017	0.000		-0.012	0.010	-0.000		0.007	0.010	0.002	
Male, age spline 35 to 44	-0.004	0.007	-0.000		0.027**	0.011	0.001		-0.006	0.013	-0.000		-0.006	0.009	-0.000		0.012	0.009	0.003	
Male, age spline 45 to 54	-0.008	0.007	-0.001		-0.014	0.009	-0.000		0.005	0.011	0.000		0.004	0.009	0.000		-0.033***	0.010	-0.009	
Male, age spline 55 to 64	-0.002	0.008	-0.000		0.021**	0.010	0.001		0.015	0.012	0.000		0.016	0.012	0.000		0.016	0.012	0.004	
Male, age spline 65 to 74	-0.017	0.011	-0.001		-0.008	0.012	-0.000		0.008	0.014	0.000		-0.034*	0.019	-0.001		0.026	0.021	0.007	
Male, age spline over 75	0.007	0.010	0.001		-0.000	0.013	-0.000		0.010	0.013	0.000		0.008	0.026	0.000		-0.041	0.040	-0.011	
Lag of Doctor ever - heart disease																	0.014	0.039	0.004	
Lag of Doctor ever - cancer																				
Lag of Doctor ever - hypertension																				
Lag of Doctor ever - diabetes	0.239***	0.032	0.024														0.065	0.048	0.018	
Lag of Ever smoked cigarettes	0.048***	0.018	0.004		0.041	0.025	0.001		0.262***	0.030	0.005		1.418***	0.028	0.063					
Lag of Current smoker	0.045**	0.023	0.004		0.035	0.032	0.001		0.260***	0.031	0.006									
Lag of Any light or heavy physical activity	-0.047**	0.022	-0.004		-0.108***	0.028	-0.003		-0.093***	0.031	-0.002		-0.157***	0.029	-0.004		0.125***	0.028	0.032	
Log(BMI) spline, BMI < 30	0.982***	0.071	0.080		1.637***	0.116	0.041		-0.025	0.102	-0.000		-0.254***	0.086	-0.005		0.246***	0.083	0.066	
Log(BMI) spline, BMI > 30	0.783***	0.081	0.064		1.182***	0.092	0.030		0.998***	0.109	0.019		-0.172	0.109	-0.004		0.231*	0.125	0.061	
Black, Less than HS	-0.037	0.050	-0.003		-0.052	0.064	-0.001		-0.169***	0.065	-0.003		-0.065	0.063	-0.001		0.115**	0.055	0.032	
Black, College	0.041	0.051	0.003		0.053	0.075	0.001		0.220**	0.086	0.006		0.247***	0.074	0.007		-0.229***	0.087	-0.055	
Black, Beyond College	0.037	0.080	0.003		0.021	0.115	0.001		0.215	0.150	0.005		0.510***	0.129	0.020		0.170	0.183	0.049	
Hispanic, Less than HS	-0.163**	0.067	-0.012		-0.087	0.085	-0.002		-0.299***	0.114	-0.004		-0.158*	0.087	-0.003		0.165*	0.099	0.047	
Hispanic, College	-0.125	0.100	-0.009		-0.114	0.142	-0.003		0.285*	0.158	0.008		0.296**	0.117	0.009		0.048	0.158	0.013	
Hispanic, Beyond College	-0.097	0.139	-0.007		-0.246	0.232	-0.005		-0.137	0.358	-0.002		0.247	0.222	0.007		-0.428	0.278	-0.092	
Lag of married from marriage history																				
Lag of cohab																				
Male, previously married																				
Male, previously cohabitating																				
Lag of Doctor ever - chronic lung disease																	-0.107***	0.040	-0.027	
_cons	-6.626***	0.328			-8.057***	0.506			-2.257***	0.452			-0.861**	0.347			-1.201***	0.348		

note: .01 - ***; .05 - **; .1 - *;

Binaries - econ

	OASI claiming (oasiclaim) coefficients		OASI claiming (oasiclaim) marginal effects		OAI claiming (oaiclaim) coefficients		OAI claiming (oaiclaim) marginal effects		DI claiming (diclaim) coefficients		DI claiming (diclaim) marginal effects		b_fullparttime_coef		b_fullparttime_mfx	
	coef	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**	**coef**	**p-value**
Age spline, less than 35	0.039***	0.011	0.001						0.018**	0.007	0.001		-0.004	0.004	-0.001	
Age spline, 35 to 44	0.012*	0.007	0.000						0.006	0.005	0.000		0.005	0.003	0.001	
Age spline, 45 to 54	-0.022***	0.006	-0.000						0.019***	0.005	0.001		-0.009***	0.003	-0.002	
Age spline, 55 to 64	0.229***	0.006	0.004		0.486***	0.045	0.167						-0.015***	0.005	-0.004	
Age spline, 65 to 74	0.082**	0.039	0.002		0.001	0.007	0.000		-2.205	5.235	-0.063		-0.028**	0.014	-0.008	
o.l2age75p	(dropped)				0.002	0.006	0.001		(dropped)				-0.085*	0.049	-0.024	
Age 60 to 61	-0.536***	0.049	-0.006		-0.313	0.218	-0.098									
Age 62 to 63	0.192***	0.039	0.004		0.369***	0.076	0.130									
Age 65 to 66	0.145**	0.063	0.003		-0.095*	0.051	-0.032									
Age 67 to 70	0.453***	0.133	0.015		0.366***	0.048	0.133									
Male	-0.256***	0.036	-0.005		-0.065	0.046	-0.022		0.085**	0.034	0.002		-0.022	0.179	-0.006	
Less than HS/GED	-0.048	0.044	-0.001		-0.325***	0.050	-0.105		0.197***	0.037	0.007		-0.015	0.039	-0.004	
College	-0.256***	0.043	-0.004		-0.141**	0.055	-0.047		-0.289***	0.050	-0.007		-0.051**	0.021	-0.015	
Beyond college	-0.349***	0.059	-0.004		-0.344***	0.068	-0.108		-0.464***	0.087	-0.009		-0.056*	0.030	-0.016	
Male, Less than HS	0.003	0.069	0.000		0.306***	0.079	0.112		0.051	0.053	0.002		-0.035	0.040	-0.010	
Male, College	0.127**	0.064	0.003		0.035	0.081	0.012		-0.121	0.076	-0.003		0.079***	0.030	0.022	
Male, Beyond College	0.224***	0.086	0.005		0.158	0.100	0.056		-0.195	0.146	-0.005		-0.053	0.043	-0.015	
Non-hispanic black	0.034	0.033	0.001		-0.169***	0.045	-0.057		0.174***	0.031	0.005		0.155***	0.021	0.043	
Hispanic	-0.137**	0.063	-0.002		0.092	0.081	0.032		-0.094	0.059	-0.002		0.065*	0.035	0.018	
Black male	0.038	0.052	0.001		0.111	0.071	0.039		-0.009	0.046	-0.000		-0.132***	0.028	-0.039	
Hispanic male	0.016	0.102	0.000		-0.177	0.125	-0.058		-0.159*	0.092	-0.004		-0.079*	0.043	-0.023	
Lag of Doctor ever - cancer	-0.049	0.055	-0.001		-0.011	0.054	-0.004		0.244***	0.057	0.009		-0.047	0.042	-0.014	
Lag of Doctor ever - diabetes	-0.032	0.037	-0.001		0.007	0.040	0.003		0.188***	0.034	0.007		0.002	0.029	0.001	
Lag of Doctor ever - heart disease	0.092***	0.034	0.002		-0.017	0.036	-0.006		0.221***	0.032	0.008		-0.035	0.026	-0.010	
Lag of Doctor ever - hypertension	0.088***	0.027	0.002		0.023	0.031	0.008		0.165***	0.026	0.005		-0.015	0.018	-0.004	
Lag of Doctor ever - chronic lung disease	0.066	0.043	0.001		-0.141***	0.049	-0.047		0.220***	0.036	0.008		0.012	0.034	0.003	
Lag of Doctor ever - stroke	-0.131*	0.073	-0.002		-0.098	0.070	-0.033		0.187***	0.060	0.007		0.045	0.083	0.013	
Lag of one ADL	0.024	0.047	0.000		-0.213***	0.048	-0.070		0.753***	0.036	0.049		-0.104***	0.040	-0.031	
Lag of two ADLs	0.062	0.064	0.001		-0.303***	0.067	-0.095		0.826***	0.047	0.059		-0.100	0.065	-0.030	
Lag of three or more ADLs	0.189***	0.060	0.004		-0.381***	0.065	-0.117		0.993***	0.044	0.083		-0.093	0.082	-0.027	
y2001	0.189***	0.046	0.004		0.334***	0.060	0.122		-0.072	0.046	-0.002					
y2003	0.145***	0.046	0.003		0.252***	0.061	0.091		-0.142***	0.046	-0.004					
y2005	0.137***	0.044	0.003		0.229***	0.059	0.082		-0.101**	0.042	-0.003					
y2007	0.046	0.044	0.001		0.269***	0.056	0.097		-0.041	0.039	-0.001					
y2009	0.119***	0.041	0.002		0.282***	0.053	0.102		-0.023	0.038	-0.001					
y2011	0.137***	0.039	0.003		0.132***	0.050	0.047		-0.037	0.037	-0.001					
y2013	0.120***	0.037	0.002		0.112**	0.046	0.039		0.029	0.036	0.001					
Age spline, 55 to 61									0.018**	0.007	0.001					
Age spline, 62 to 64									-0.069**	0.029	-0.002					
Lag of any socical security disability income LCY									2.339***	0.030	0.480		-0.297***	0.081	-0.094	
under65_lowincome																
under65_lowwealth																
under65_l2age35l																
under65_l2age3544																
under65_l2age4554																
under65_l2age5564																
under65_male																
under65_black																

Binaries - relationship

	b_exitsingle_m_coef		b_exitsingle_m_mfx		b_exitsingle_f_coef		b_exitsingle_f_mfx		b_single2married_m_coef		b_single2married_m_mfx		b_single2married_f_coef		b_single2married_f_mfx	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Lag of Ever Married	0.433***	0.116	0.088		0.085	0.086	0.008		0.669***	0.254	0.261		0.291	0.235	0.116	
Lag of Ever seperated from marriage or cohabitation	-0.203*	0.107	-0.039		0.193**	0.080	0.020		-0.388	0.238	-0.150		0.075	0.225	0.030	
Non-hispanic black	-0.258***	0.075	-0.049		-0.640***	0.065	-0.068		0.146*	0.089	0.058		0.497***	0.078	0.196	
Hispanic	-0.107	0.159	-0.020		-0.186	0.116	-0.016		0.056	0.181	0.022		0.156	0.133	0.062	
Less than HS/GED	0.113**	0.053	0.023		-0.084*	0.047	-0.008		-0.188	0.117	-0.073		-0.158	0.114	-0.063	
College	0.083*	0.048	0.017		0.139***	0.041	0.015		0.351***	0.100	0.139		0.314***	0.090	0.124	
Beyond college	0.193**	0.075	0.042		0.232***	0.061	0.027		0.538***	0.159	0.212		0.460***	0.130	0.179	
Lag of Unemployed	-0.005	0.080	-0.001		-0.007	0.062	-0.001		-0.387**	0.188	-0.145		-0.198	0.141	-0.079	
Lag of Part-time	0.079	0.076	0.016		-0.015	0.060	-0.002		-0.026	0.169	-0.010		-0.042	0.133	-0.017	
Lag of Full-time	0.116	0.077	0.023		0.021	0.063	0.002		-0.074	0.171	-0.029		-0.003	0.140	-0.001	
Lag of IHS of iearnx divided by 100	4.689***	1.735	0.921		1.683	1.545	0.168		10.624***	3.847	4.171		5.322	3.554	2.123	
Lag of IHS of hatotbx divided by 100	0.952*	0.559	0.187		-1.031**	0.448	-0.103		-0.054	1.162	-0.021		2.375**	0.964	0.947	
R's mother high school grad	-0.045	0.049	-0.009		-0.020	0.037	-0.002		-0.032	0.105	-0.013		0.179**	0.089	0.071	
R;s mother some college	-0.068	0.061	-0.013		0.048	0.047	0.005		0.042	0.128	0.017		0.143	0.107	0.057	
R's mother college graduate	-0.112*	0.061	-0.021		0.013	0.051	0.001		-0.072	0.129	-0.028		0.051	0.113	0.020	
Lag of 1 biological child	0.114**	0.055	0.023		-0.006	0.048	-0.001		-0.124	0.118	-0.048		-0.187*	0.106	-0.074	
Lag of 2 biological children	0.242***	0.058	0.052		0.003	0.048	0.000		-0.214*	0.121	-0.083		0.060	0.107	0.024	
Lag of 3 or more biological children	0.256***	0.061	0.055		0.111**	0.049	0.011		0.005	0.130	0.002		0.152	0.112	0.061	
Age 30 to 34	-0.020	0.066	-0.004		-0.145**	0.064	-0.013		-0.038	0.099	-0.015		0.010	0.089	0.004	
Age 35 to 39	-0.377***	0.080	-0.062		-0.456***	0.073	-0.034		-0.033	0.125	-0.013		-0.034	0.109	-0.014	
Age 40 to 49	-0.732***	0.077	-0.109		-0.827***	0.069	-0.057		0.055	0.135	0.022		-0.130	0.109	-0.052	
Age 50 to 59	-1.016***	0.086	-0.134		-1.283***	0.080	-0.072									
Age 60 to 64	-1.415***	0.136	-0.130		-1.523***	0.121	-0.057									
Age more than 65	-1.435***	0.123	-0.146		-1.945***	0.108	-0.104									
Black, age 30 to 34	0.051	0.106	0.010		0.021	0.090	0.002									
Black, age 35 to 39	0.220*	0.122	0.048		0.196**	0.098	0.023									
Black, age 40 to 49	0.155	0.111	0.033		0.312***	0.089	0.038									
Black, age 50 to 59	0.049	0.126	0.010		0.342***	0.107	0.043									
Black, age 60 to 64	0.390*	0.202	0.094		0.283	0.191	0.035									
Black, age more than 65	-0.003	0.234	-0.001		0.369**	0.184	0.048									
Hispanic, age 30 to 34	-0.394	0.242	-0.061		-0.153	0.173	-0.013									
Hispanic, age 35 to 39	-0.038	0.242	-0.007		-0.306	0.213	-0.024									
Hispanic, age 40 to 49	-0.346	0.263	-0.055		0.050	0.172	0.005									
Hispanic, age 50 to 59	0.260	0.279	0.059		0.121	0.202	0.013									
Hispanic, age more than 60	-0.005	0.314	-0.001		-0.067	0.294	-0.006									
Age more than 50									0.104	0.155	0.041		-0.200	0.138	-0.079	
Black, age more than 50																
Hispanic, age more than 50																
Hispanic, age 60 to 64																
Hispanic, age more than 65																
_cons	-0.965***	0.083			-0.686***	0.069			-0.674***	0.176			-0.709***	0.142		

note: .01 - ***; .05 - **; .1 - *;

Ordered probits

	ADL status (adlstat) coefficients		ADL status (adlstat) marginal effects						IADL status (iadlstat) coefficients		IADL status (iadlstat) marginal effects					
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-hispanic black	-0.012	0.022	0.001		-0.001		-0.000		-0.000		-0.083***	0.021	0.011		-0.008		-0.003	
Hispanic	-0.011	0.043	0.001		-0.001		-0.000		-0.000		-0.005	0.040	0.001		-0.000		-0.000	
Less than HS/GED	0.105***	0.026	-0.013		0.009		0.003		0.002		0.095***	0.026	-0.013		0.010		0.003	
College	-0.175***	0.023	0.019		-0.013		-0.004		-0.002		-0.133***	0.022	0.017		-0.013		-0.004	
Beyond college	-0.204***	0.032	0.021		-0.015		-0.005		-0.002		-0.133***	0.030	0.016		-0.013		-0.004	
Black, Less than HS	-0.001	0.038	0.000		-0.000		-0.000		-0.000		-0.002	0.037	0.000		-0.000		-0.000	
Black, College	0.044	0.049	-0.005		0.004		0.001		0.001		-0.019	0.048	0.002		-0.002		-0.001	
Black, Beyond College	0.014	0.077	-0.002		0.001		0.000		0.000		-0.088	0.077	0.011		-0.008		-0.003	
Hispanic, Less than HS	0.013	0.057	-0.002		0.001		0.000		0.000		-0.047	0.054	0.006		-0.005		-0.001	
Hispanic, College	0.222***	0.085	-0.031		0.020		0.007		0.004		0.208***	0.077	-0.032		0.024		0.008	
Hispanic, Beyond College	-0.014	0.141	0.002		-0.001		-0.000		-0.000		-0.022	0.120	0.003		-0.002		-0.001	
Male	0.316	0.309	-0.039		0.026		0.009		0.004		0.103	0.286	-0.014		0.010		0.003	
Black male	0.028	0.030	-0.003		0.002		0.001		0.000		0.093***	0.030	-0.013		0.010		0.003	
Hispanic male	-0.160***	0.052	0.017		-0.012		-0.004		-0.002		0.008	0.048	-0.001		0.001		0.000	
Poor as a child	0.059***	0.015	-0.007		0.005		0.002		0.001		0.051***	0.015	-0.007		0.005		0.002	
Wealthy as a child	0.042**	0.019	-0.005		0.003		0.001		0.001		0.041**	0.018	-0.006		0.004		0.001	
Childhood health - fair	-0.048	0.058	0.006		-0.004		-0.001		-0.001		-0.025	0.057	0.003		-0.002		-0.001	
Childhood health - good	-0.188***	0.052	0.020		-0.014		-0.004		-0.002		-0.195***	0.051	0.023		-0.018		-0.005	
Childhood health - very good	-0.227***	0.051	0.025		-0.017		-0.006		-0.003		-0.208***	0.050	0.026		-0.020		-0.006	
Childhood health - excellent	-0.263***	0.050	0.033		-0.021		-0.007		-0.004		-0.276***	0.049	0.038		-0.029		-0.009	
Age spline, less than 35	0.029***	0.006	-0.003		0.002		0.001		0.000		0.021***	0.006	-0.003		0.002		0.001	
Age spline, 35 to 44	0.014***	0.004	-0.002		0.001		0.000		0.000		0.014***	0.004	-0.002		0.001		0.000	
Age spline, 45 to 54	0.013***	0.004	-0.002		0.001		0.000		0.000		0.014***	0.004	-0.002		0.001		0.000	
Age spline, 55 to 64	0.007*	0.004	-0.001		0.001		0.000		0.000		0.003	0.004	-0.000		0.000		0.000	
Age spline, 65 to 74	0.018***	0.005	-0.002		0.001		0.000		0.000		0.004	0.004	-0.001		0.000		0.000	
Age spline, more than 75	0.042***	0.004	-0.005		0.003		0.001		0.001		0.028***	0.004	-0.004		0.003		0.001	
Male, age spline less than 35	-0.014	0.010	0.002		-0.001		-0.000		-0.000		-0.010	0.010	0.001		-0.001		-0.000	
Male, age spline 35 to 44	0.003	0.007	-0.000		0.000		0.000		0.000		-0.006	0.007	0.001		-0.001		-0.000	
Male, age spline 45 to 54	0.005	0.006	-0.001		0.000		0.000		0.000		0.006	0.006	-0.001		0.001		0.000	
Male, age spline 55 to 64	0.001	0.006	-0.000		0.000		0.000		0.000		0.003	0.006	-0.000		0.000		0.000	
Male, age spline 65 to 74	-0.011	0.007	0.001		-0.001		-0.000		-0.000		-0.002	0.007	0.000		-0.000		-0.000	
Male, age spline over 75	0.009	0.006	-0.001		0.001		0.000		0.000		0.014**	0.006	-0.002		0.001		0.000	
Lag of Doctor ever - heart disease	0.161***	0.018	-0.021		0.014		0.005		0.003		0.155***	0.018	-0.023		0.017		0.006	
Lag of Doctor ever - stroke	0.258***	0.034	-0.037		0.024		0.009		0.005		0.183***	0.034	-0.028		0.020		0.007	
Lag of Doctor ever - cancer	0.139***	0.029	-0.018		0.012		0.004		0.002		0.166***	0.029	-0.025		0.018		0.006	
Lag of Doctor ever - hypertension	0.182***	0.016	-0.024		0.016		0.005		0.003		0.182***	0.016	-0.026		0.020		0.006	
Lag of Doctor ever - diabetes	0.140***	0.020	-0.018		0.012		0.004		0.002		0.138***	0.021	-0.020		0.015		0.005	
Lag of Doctor ever - chronic lung disease	0.232***	0.022	-0.033		0.021		0.008		0.004		0.227***	0.022	-0.035		0.026		0.009	
Lag of one ADL	1.146***	0.020	-0.269		0.137		0.072		0.061		0.537***	0.022	-0.100		0.070		0.030	
Lag of two ADLs	1.640***	0.027	-0.465		0.185		0.127		0.153		0.713***	0.030	-0.149		0.100		0.048	
Lag of three or more ADLs	2.280***	0.028	-0.695		0.178		0.172		0.345		0.831***	0.032	-0.184		0.121		0.063	
Lag of Ever smoked cigarettes	0.095***	0.015	-0.011		0.008		0.003		0.001		0.076***	0.015	-0.010		0.008		0.002	
Lag of Current smoker	0.175***	0.019	-0.023		0.015		0.005		0.003		0.189***	0.018	-0.027		0.021		0.007	
Lag of Any light or heavy physical activity	-0.195***	0.016	0.026		-0.017		-0.006		-0.003		-0.147***	0.016	0.021		-0.016		-0.005	
Log(BMI) spline, BMI < 30	0.138**	0.057	-0.017		0.011		0.004		0.002		-0.011	0.054	0.001		-0.001		-0.000	
Log(BMI) spline, BMI > 30	0.816***	0.060	-0.098		0.065		0.022		0.011		0.466***	0.061	-0.062		0.047		0.015	
Lag of one IADL									0.920***	0.019	-0.205		0.133		0.072	
Lag of two or more IADLs									1.399***	0.027	-0.383		0.211		0.172	

	Number of new children (births) coefficients		Number of new children (births) marginal effects						Number of new children (paternity) coefficients		Number of new children (paternity) marginal effects					
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-hispanic black	-0.017	0.025	0.003		-0.003		-0.000		0.039	0.026	-0.004		0.004		0.000	
Hispanic	0.047	0.036	-0.008		0.008		0.000		0.070*	0.038	-0.007		0.007		0.000	
Less than HS/GED	0.124***	0.036	-0.023		0.022		0.001		0.040	0.035	-0.004		0.004		0.000	
College	0.116***	0.026	-0.021		0.021		0.001		0.093***	0.027	-0.010		0.010		0.000	
Beyond college	0.181***	0.038	-0.035		0.033		0.002		0.222***	0.043	-0.026		0.026		0.001	
Lag of Doctor ever - cancer	-0.127	0.112	0.021		-0.020		-0.001									
Lag of	0.169***	0.021	-0.030		0.029		0.001		0.107***	0.015	-0.011		0.011		0.000	
l2age^2	-0.004***	0.000	0.001		-0.001		-0.000		-0.003***	0.000	0.000		-0.000		-0.000	
Lag of 1 biological child	0.295***	0.028	-0.058		0.055		0.003		0.237***	0.028	-0.027		0.026		0.001	
Lag of 2 biological children	-0.171***	0.030	0.029		-0.028		-0.001		-0.214***	0.030	0.020		-0.020		-0.000	
Lag of 3 or more biological children	-0.200***	0.034	0.033		-0.032		-0.001		-0.119***	0.034	0.011		-0.011		-0.000	
Lag of married from marriage history	0.612***	0.027	-0.103		0.099		0.004		0.863***	0.033	-0.072		0.070		0.002	
Lag of cohab	0.222***	0.036	-0.044		0.042		0.002		0.490***	0.040	-0.068		0.065		0.002	
Lag of Unemployed	-0.043	0.045	0.007		-0.007		-0.000		0.018	0.060	-0.002		0.002		0.000	
Lag of Part-time	-0.108***	0.029	0.018		-0.018		-0.001		-0.008	0.051	0.001		-0.001		-0.000	
Lag of Full-time	-0.131***	0.026	0.023		-0.022		-0.001		-0.004	0.045	0.000		-0.000		-0.000	
R's mother high school grad	0.022	0.030	-0.004		0.004		0.000		-0.028	0.032	0.003		-0.003		-0.000	
R;s mother some college	0.093***	0.034	-0.017		0.016		0.001		-0.007	0.039	0.001		-0.001		-0.000	
R's mother college graduate	0.113***	0.036	-0.021		0.020		0.001		0.045	0.038	-0.005		0.005		0.000	

Supplement_2_FAM_estimates

	Log(BMI) (logbmi) women - coefficients		Log(BMI) (logbmi) - women - marginal effects		Log(BMI) (logbmi) men - coefficients		Log(BMI) (logbmi) - men - marginal effects		SSDI amount (ssdiamt) coefficients		SSDI amount (ssdiamt) marginal effects		OASI amount (ssdiamt) coefficients		OASI amount (ssdiamt) marginal effects		OAI amount (ssdiamt) coefficients		OAI amount (ssdiamt) marginal effects	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-hispanic black	0.009***	0.001	0.009		0.001	0.001	0.001													
Hispanic	0.003	0.002	0.003		0.002	0.002	0.002													
Less than HS/GED	0.002	0.002	0.002		-0.001	0.002	-0.001		-2,025.646***	279.232	-2,025.646		-2,082.145***	178.583	########		-2,270.824***	202.408	########	
College	-0.008***	0.001	-0.008		-0.006***	0.001	-0.006		2,590.571***	486.321	2,590.571		1,357.451***	201.883	1,357.451		1,480.943***	210.377	1,480.943	
Beyond college	-0.008***	0.002	-0.008		-0.005***	0.002	-0.005		3,510.543***	959.881	3,510.543		2,206.006***	273.834	2,206.006		2,381.822***	283.145	2,381.822	
Black, Less than HS	-0.008***	0.003	-0.008		-0.005**	0.002	-0.005													
Black, College	0.004*	0.003	0.004		0.005**	0.003	0.005													
Black, Beyond College	0.005	0.004	0.005		0.006	0.005	0.006													
Hispanic, Less than HS	-0.002	0.004	-0.002		-0.004	0.003	-0.004													
Hispanic, College	0.006	0.005	0.006		-0.003	0.005	-0.003													
Hispanic, Beyond College	0.003	0.007	0.003		-0.006	0.006	-0.006													
Poor as a child	0.001	0.001	0.001		0.001*	0.001	0.001													
Wealthy as a child	-0.001	0.001	-0.001		-0.002	0.001	-0.002													
Childhood health - fair	0.004	0.004	0.004		0.004	0.004	0.004													
Childhood health - good	0.001	0.004	0.001		0.004	0.004	0.004													
Childhood health - very good	0.001	0.004	0.001		0.003	0.004	0.003													
Childhood health - excellent	-0.001	0.004	-0.001		0.002	0.004	0.002													
Age spline, less than 35	-0.000	0.000	-0.000		-0.000	0.000	-0.000		294.574***	82.992	294.574		571.624**	225.225	571.624					
Age spline, 35 to 44	-0.000*	0.000	-0.000		-0.000*	0.000	-0.000		110.305**	49.002	110.305		289.871**	125.099	289.871					
Age spline, 45 to 54	-0.000*	0.000	-0.000		-0.001***	0.000	-0.001		28.105	37.510	28.105		-272.249***	95.801	-272.249					
Age spline, 55 to 64	-0.000*	0.000	-0.000		-0.000	0.000	-0.000		158.855***	38.337	158.855		146.594***	52.232	146.594		1,891.647***	144.217	1,891.647	
Age spline, 65 to 74	-0.001***	0.000	-0.001		-0.001***	0.000	-0.001		16,911.703	31,182.962	16,911.703		119.599***	17.376	119.599		45.937**	18.820	45.937	
Age spline, more than 75	-0.002***	0.000	-0.002		-0.002***	0.000	-0.002						-67.394***	13.397	-67.394		-61.801***	14.150	-61.801	
l2logbmi: (.,2.9957323)	0.795***	0.020	0.795		0.225***	0.032	0.225													
l2logbmi: (2.995732273553991,3.2188758)	0.941***	0.008	0.941		0.939***	0.009	0.939													
l2logbmi: (3.218875824868201,3.4011974)	0.914***	0.009	0.914		0.913***	0.007	0.913													
l2logbmi: (3.401197381662155,3.5553481)	0.923***	0.014	0.923		0.924***	0.012	0.924													
l2logbmi: (3.555348061489414,3.6888795)	0.866***	0.020	0.866		0.866***	0.022	0.866													
l2logbmi: (3.688879454113936,.)	0.803***	0.014	0.803		0.732***	0.019	0.732													
Lag of married from marriage history	-0.008***	0.001	-0.008		-0.000	0.001	-0.000													
Lag of cohab	-0.003*	0.002	-0.003		-0.000	0.001	-0.000													
Male									2,819.170***	225.829	2,819.170		3,665.217***	140.275	3,665.217		3,978.285***	143.390	3,978.285	
Black male																				
Hispanic male																				
Lag of Doctor ever - heart disease																				
Lag of Doctor ever - stroke																				
Lag of Doctor ever - cancer																				
Lag of Doctor ever - hypertension																				
Lag of Doctor ever - diabetes																				
Lag of Doctor ever - chronic lung disease																				
Lag of one ADL																				
Lag of two ADLs																				
Lag of three or more ADLs																				
Lag of Ever smoked cigarettes																				
Lag of any socical security disability income LCY																				
Lag of any social security OASI income LCY																				
Lag of social security retirement income (incl. dep.) LCY																				
Lag of Unemployed																				
Lag of Part-time																				
Lag of Full-time																				
Lag of IHS of iearnx divided by 100																				
Lag of IHS of hatotbx divided by 100																				
Lag of Current smoker																				
Lag of any SSI LCY																				
Married- from individual file																				
Cohabitating																				
Earnings in thousands in 2009 dollars. This will be used in the simulation with capital income in 2009 dollars. This will be used in the simulation without inf																				
o.l2age75p									(dropped)											
Male, Less than HS									-604.342	412.948	-604.342		-937.183***	276.992	-937.183		-844.130***	292.007	-844.130	
Male, College									1,807.243**	742.683	1,807.243		-209.655	285.768	-209.655		-296.466	289.280	-296.466	
Male, Beyond College									-5,246.815***	1,657.408	-5,246.815		299.299	369.072	299.299		279.150	372.570	279.150	
o.l2age35l																	(dropped)			
o.l2age3544																	(dropped)			
o.l2age4554																	(dropped)			
Lag of Any light or heavy physical activity																				
_cons	0.658***	0.060			2.356***	0.096			-1,486.582	2,513.140			-10,657.852	6,902.362			-8,786.470***	1,385.898		

note: .01 - ***; .05 - **; .1 - *;

	ml_laborforcestat_coef						ml_laborforcestat_mfx					
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-hispanic black	-0.017	0.039	0.674***	0.057			-0.007		0.028			
Hispanic	0.205***	0.063	0.405***	0.098			0.028		0.015			
Less than HS/GED	0.355***	0.060	0.393***	0.089			0.052		0.013			
College	-0.009	0.041	-0.114	0.082			-0.001		-0.004			
Beyond college	-0.110*	0.062	-0.381***	0.140			-0.013		-0.011			
Black, Less than HS	-0.028	0.073	0.123	0.092			-0.005		0.005			
Black, College	-0.133	0.082	-0.531***	0.120			-0.016		-0.014			
Black, Beyond College	-0.129	0.136	-0.171	0.202			-0.017		-0.005			
Hispanic, Less than HS	-0.083	0.096	0.002	0.128			-0.012		0.001			
Hispanic, College	-0.065	0.133	-0.581**	0.235			-0.006		-0.016			
Hispanic, Beyond College	-0.130	0.215	0.146	0.299			-0.019		0.006			
Male	-0.445	0.455	-0.026	0.430			-0.063		0.002			
Black male	0.152***	0.058	-0.050	0.073			0.023		-0.003			
Hispanic male	-0.519***	0.096	-0.064	0.114			-0.063		0.000			
Poor as a child	0.050*	0.026	0.061	0.037			0.007		0.002			
Wealthy as a child	0.035	0.030	0.029	0.040			0.005		0.001			
Childhood health - fair	0.099	0.118	-0.023	0.159			0.015		-0.001			
Childhood health - good	-0.043	0.106	-0.132	0.144			-0.005		-0.004			
Childhood health - very good	0.016	0.105	-0.145	0.142			0.003		-0.005			
Childhood health - excellent	0.025	0.103	-0.130	0.140			0.004		-0.005			
Age spline, less than 35	-0.011	0.008	-0.007	0.010			-0.002		-0.000			
Age spline, 35 to 44	-0.020***	0.006	-0.015*	0.009			-0.003		-0.000			
Age spline, 45 to 54	0.034***	0.006	-0.002	0.010			0.005		-0.000			
Age spline, 55 to 64	0.148***	0.007	-0.002	0.016			0.021		-0.001			
Age spline, 65 to 74	0.030**	0.013	-0.123***	0.047			0.005		-0.005			
Age spline, more than 75	0.164***	0.024	0.137**	0.065			0.023		0.004			
Lag of Doctor ever - heart disease	0.089**	0.040	0.048	0.069			0.013		0.001			
Lag of Doctor ever - stroke	0.579***	0.102	0.186	0.173			0.097		0.002			
Lag of Doctor ever - cancer	0.030	0.063	-0.235	0.156			0.006		-0.008			
Lag of Doctor ever - hypertension	0.224***	0.030	-0.160***	0.051			0.035		-0.007			
Lag of Doctor ever - diabetes	0.225***	0.045	-0.144*	0.084			0.035		-0.006			
Lag of Doctor ever - chronic lung disease	0.299***	0.051	0.107	0.075			0.046		0.002			
Lag of one ADL	0.445***	0.055	0.158*	0.089			0.071		0.002			
Lag of two ADLs	0.672***	0.081	0.145	0.133			0.116		-0.000			
Lag of three or more ADLs	1.106***	0.091	0.231	0.149			0.210		-0.003			
Lag of Ever smoked cigarettes	0.012	0.026	0.186***	0.040			0.001		0.007			
Lag of Current smoker	0.188***	0.033	0.325***	0.042			0.026		0.011			
Lag of any socical security disability income LCY	1.070***	0.072	0.121	0.118			0.202		-0.006			
Lag of any SSI LCY	1.384***	0.096	0.718***	0.124			0.269		0.012			
Lag of any social security OASI income LCY	0.244**	0.104	-0.135	0.193			0.038		-0.006			
Lag of social security retirement income (incl. dep.) LCY	-0.421***	0.110	-0.321	0.282			-0.053		-0.008			
Lag of Unemployed	-1.162***	0.045	0.638***	0.055			-0.120		0.038			
Lag of Part-time	-1.989***	0.035	-0.570***	0.059			-0.189		-0.011			
Lag of Full-time	-2.484***	0.038	-0.987***	0.062			-0.362		-0.015			
Lag of IHS of iearnx divided by 100	-33.045***	0.880	-23.445***	1.363			-4.610		-0.616			
Lag of IHS of hatotbx divided by 100	2.384***	0.397	-4.047***	0.508			0.369		-0.158			
Male, age spline less than 35	-0.001	0.016	0.004	0.015			-0.000		0.000			
Male, age spline 35 to 44	0.038***	0.012	0.022*	0.013			0.005		0.001			
Male, age spline 45 to 54	0.034***	0.011	0.014	0.014			0.005		0.000			
Male, age spline 55 to 64	0.039***	0.011	-0.032	0.023			0.006		-0.001			
Male, age spline 65 to 74	-0.011	0.015	0.056	0.065			-0.002		0.002			
Male, age spline over 75	-0.072**	0.031	-0.955	0.792			-0.004		-0.033			
Male, Less than HS	-0.177**	0.070	-0.054	0.079			-0.024		-0.001			
Male, College	-0.050	0.065	0.092	0.103			-0.008		0.004			
Male, Beyond College	0.007	0.093	0.124	0.175			0.000		0.005			
Lag of married from marriage history	0.462***	0.036	-0.542***	0.051			0.067		-0.024			
Lag of cohab	0.268***	0.058	-0.268***	0.076			0.043		-0.010			

Male, previously married	-0.650***	0.061	0.056	0.074		-0.087	0.006	
Male, previously cohabitating	-0.425***	0.098	0.219**	0.102		-0.055	0.011	
Log(BMI) spline, BMI < 30	-0.434***	0.092	-0.081	0.132		-0.062	-0.000	
Log(BMI) spline, BMI > 30	0.415***	0.123	0.192	0.166		0.059	0.004	
o.black					(dropped)			-0.020
o.hispan					(dropped)			-0.043
o.educ1					(dropped)			-0.065
o.educ3					(dropped)			0.004
o.educ4					(dropped)			0.025
o.black_educ1					(dropped)			-0.000
o.black_educ3					(dropped)			0.030
o.black_educ4					(dropped)			0.022
o.hispan_educ1					(dropped)			0.011
o.hispan_educ3					(dropped)			0.022
o.hispan_educ4					(dropped)			0.012
o.male					(dropped)			0.061
o.male_black					(dropped)			-0.020
o.male_hispan					(dropped)			0.063
o.fpoor					(dropped)			-0.009
o.frich					(dropped)			-0.006
o.chldsrh2					(dropped)			-0.013
o.chldsrh3					(dropped)			0.010
o.chldsrh4					(dropped)			0.002
o.chldsrh5					(dropped)			0.000
o.l2age35l					(dropped)			0.002
o.l2age3544					(dropped)			0.003
o.l2age4554					(dropped)			-0.005
o.l2age5564					(dropped)			-0.020
o.l2age6574					(dropped)			-0.001
o.l2age75p					(dropped)			-0.027
o.l2hearte					(dropped)			-0.014
o.l2stroke					(dropped)			-0.099
o.l2cancre					(dropped)			0.002
o.l2hibpe					(dropped)			-0.028
o.l2diabe					(dropped)			-0.029
o.l2lunge					(dropped)			-0.048
o.l2adl1					(dropped)			-0.074
o.l2adl2					(dropped)			-0.116
o.l2adl3p					(dropped)			-0.208
o.l2smokev					(dropped)			-0.007
o.l2smoken					(dropped)			-0.037
o.l2diclaim					(dropped)			-0.197
o.l2ssiclaim					(dropped)			-0.281
o.l2oasiclaim					(dropped)			-0.032
o.l2oaiclaim					(dropped)			0.061
o.l2workcat2					(dropped)			0.082
o.l2workcat3					(dropped)			0.200
o.l2workcat4					(dropped)			0.377
o.l2logiearnx					(dropped)			5.227
o.l2loghatotbx					(dropped)			-0.211
o.l2age35l_male					(dropped)			0.000
o.l2age3544_male					(dropped)			-0.006
o.l2age4554_male					(dropped)			-0.005
o.l2age5564_male					(dropped)			-0.004
o.l2age6574_male					(dropped)			-0.000
o.l2age75p_male					(dropped)			0.037
o.male_educ1					(dropped)			0.025
o.male_educ3					(dropped)			0.004
o.male_educ4					(dropped)			-0.005
o.l2married					(dropped)			-0.043
o.l2cohab					(dropped)			-0.033
o.male_l2married					(dropped)			0.081
o.male_l2cohab					(dropped)			0.044
o.l2logbmi_l30					(dropped)			0.062
o.l2logbmi_30p					(dropped)			-0.063
_cons	2.069***	0.377	-0.827	0.521				
Lag of Uninsured								
Lag of Public Insurance Only								
Age spline, more than 55								
o.l2inscat1								

o.l2inscat2	
o.l2age55p	
o._cons	(dropped)
_cons	

note: .01 - ***; .05 - **; .1 - *;

	Died (died) coefficients		Died (died) marginal effects		Partner died (part_died) coefficients		Partner died (part_died) marginal effects		R live in nursing home at interview (nhmliv) coefficients		R live in nursing home at interview (nhmliv) marginal effects	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-hispanic black	0.030	0.018	0.001		0.347	0.260	0.004		-0.231***	0.034	-0.003	
Hispanic	-0.155***	0.028	-0.005		0.166	0.432	0.002		-0.444***	0.050	-0.004	
Less than HS or GED education	0.051***	0.017	0.002		0.175***	0.053	0.002		0.029	0.024	0.000	
College degree or higher	-0.056***	0.017	-0.002		-0.163***	0.050	-0.001		-0.056**	0.024	-0.001	
Male	-0.488	0.565	-0.018		0.134	0.288	0.001		-0.113***	0.024	-0.001	
Black male	0.054**	0.027	0.002		0.166	0.448	0.002		0.423***	0.054	0.009	
Hispanic male	0.069*	0.040	0.003		1.401*	0.749	0.080		0.336***	0.077	0.007	
Age spline, less than 35	-0.010	0.014	-0.000									
Age spline, 35 to 44	0.033***	0.011	0.001						-0.123	0.245	-0.002	
Age spline, 45 to 54	0.017**	0.007	0.001						-0.052**	0.025	-0.001	
Age spline, 55 to 64	0.020***	0.004	0.001						0.045***	0.008	0.001	
Age spline, 65 to 74	0.032***	0.003	0.001		0.062***	0.009	0.001		0.040***	0.004	0.001	
Age spline, 75 to 84	0.047***	0.003	0.002									
Age spline, more than 85	0.064***	0.003	0.002									
male_l2age35l	0.025	0.019	0.001									
male_l2age3544	-0.026*	0.015	-0.001									
male_l2age4554	0.010	0.010	0.000									
male_l2age5564	0.006	0.006	0.000									
Male, age 65 to 74	-0.001	0.004	-0.000		-0.024*	0.014	-0.000					
male_l2age7584	-0.005	0.004	-0.000									
male_l2age85p	0.011**	0.005	0.000									
Lag of Doctor ever - heart disease	0.184***	0.011	0.008						-0.045**	0.021	-0.001	
Lag of Doctor ever - stroke	0.235***	0.015	0.011						0.380***	0.024	0.008	
Lag of Doctor ever - cancer	0.400***	0.013	0.022						-0.050**	0.025	-0.001	
Lag of Doctor ever - hypertension	0.122***	0.011	0.005						-0.052**	0.021	-0.001	
Lag of Doctor ever - diabetes	0.209***	0.012	0.009						0.151***	0.023	0.002	
Lag of Doctor ever - chronic lung disease	0.338***	0.014	0.018						-0.059*	0.031	-0.001	
Lag of one ADL	0.280***	0.016	0.014						0.372***	0.028	0.008	
Lag of two ADLs	0.419***	0.021	0.025						0.677***	0.034	0.021	
Lag of three or more ADLs	0.801***	0.015	0.067						1.219***	0.025	0.069	
Lag of Current smoker	0.301***	0.014	0.015						0.117***	0.033	0.002	
Male, less than high school	0.015	0.025	0.001		-0.040	0.089	-0.000					
Male, college or more	-0.048*	0.025	-0.002		0.129	0.083	0.001					
Age spline, less than 65					0.032***	0.003	0.000					
Age spline, more than 75					0.021**	0.009	0.000		0.063***	0.002	0.001	
Male, less than 65					-0.009*	0.005	-0.000					
Male, age more than 75					0.026**	0.012	0.000					
Black, age spline less than 65					0.001	0.005	0.000					
Black, age spline 65 to 74					-0.046**	0.019	-0.000					
Black, age spline over 75					0.060**	0.027	0.001					
Hispanic, age spline less than 65					-0.004	0.009	-0.000					
Hispanic, age spline 65 to 74					-0.016	0.032	-0.000					
Hispanic, age spline over 75					0.047	0.045	0.000					
Black male, less than 65					-0.008	0.009	-0.000					
Black male, 65 to 74					0.032	0.033	0.000					
Black male, over 75					-0.029	0.041	-0.000					
Hispanic male, less than 65					-0.038**	0.018	-0.000					
Hispanic male, 65 to 74					0.123*	0.070	0.001					
Hispanic male, over 75					-0.070	0.068	-0.001					
Lag of Widowed: most recent spouse died									0.229***	0.022	0.004	
o.black					(dropped)							
o.hispan					(dropped)							
o.l2age35l									(dropped)			
_cons	-2.895***	0.403			-4.092***	0.173			-1.594	2.350		

note: .01 - ***; .05 - **; .1 - *;

The Future Elderly Model: Technical Documentation

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This appendix describes technical details to support the paper **"The Effect of US COVID-19 Excess Mortality on Social Security Outlays"**.

1 Functioning of the dynamic model

1.1 Background

The Future Elderly Model (FEM) is a microsimulation model originally developed out of an effort to examine health and health care costs among the elderly Medicare population (age 65+). A description of the previous incarnation of the model can be found in Goldman et al. (2004). The original work was founded by the Centers for Medicare and Medicaid Services and carried out by a team of researchers composed of Dana P. Goldman, Paul G. Shekelle, Jayanta Bhattacharya, Michael Hurd, Geoffrey F. Joyce, Darius N. Lakdawalla, Dawn H. Matsui, Sydne J. Newberry, Constantijn W. A. Panis and Baoping Shang.

Since then various extensions have been implemented to the original model. The most recent version now projects health outcomes for all Americans aged 51 and older and uses the Health and Retirement Study (HRS) as a host dataset rather than the Medicare Current Beneficiary Survey (MCBS). The work has also been extended to include economic outcomes such as earnings, labor force participation and pensions. This work was funded by the National Institute on Aging

through its support of the RAND Roybal Center for Health Policy Simulation (P30AG024968), the Department of Labor through contract J-9-P-2-0033, the National Institutes of Aging through the R01 grant "Integrated Retirement Modeling" (R01AG030824) and the MacArthur Foundation Research Network on an Aging Society. Finally, the computer code of the model was transferred from Stata to C++. This report incorporates these new development efforts in the description of the model.

1.2 Overview

The defining characteristic of the model is the modeling of real rather than synthetic cohorts, all of whom are followed at the individual level. This allows for more heterogeneity in behavior than would be allowed by a cell-based approach. Also, since the HRS interviews both respondent and spouse, we can link records to calculate household-level outcomes such as net income and Social Security retirement benefits, which depend on the outcomes of both spouses. The omission of the population younger than age 51 sacrifices little generality, since the bulk of expenditure on the public programs we consider occurs after age 50. However, we may fail to capture behavioral responses among the young.

The model has three core components:

- The initial cohort module predicts the economic and health outcomes of new cohorts of 51/52 year-olds. This module takes in data from the Health and Retirement Study (HRS) and trends calculated from other sources. It allows us to "generate" cohorts as the simulation proceeds, so that we can measure outcomes for the age 51+ population in any given year.

- The transition module calculates the probabilities of transiting across various health states and financial outcomes. The module takes as inputs risk factors such as smoking, weight, age and education, along with lagged health and financial states. This allows for a great deal of heterogeneity and fairly general feedback effects. The transition probabilities are estimated from the longitudinal data in the Health and Retirement Study (HRS).

- The policy outcomes module aggregates projections of individual-level outcomes into policy outcomes such as taxes, medical care costs, pension benefits paid, and disability benefits. This component takes account of public and private program rules to the extent allowed by the available outcomes. Because we have access to HRS-linked restricted data from Social Security records and employer pension plans, we are able to realistically model retirement benefit receipt.

Figure 1 provides a schematic overview of the model. This population simulation example starts in 2004 with an initial population aged 51+ taken from the HRS. We then predict outcomes using our estimated transition probabilities (See section 4). Those who survive make it to the end of that year, at which point we calculate policy outcomes for the year. We then move to the following time period (two years later), when a new cohort of 51 and 52 year-olds enters in case of a population simulation. This entrance forms the new age 51+ population, which then proceeds through the transition model as before. This process is repeated until we reach the final year of the simulation. In this paper we use a cohort simulation without new cohorts entering the simulation.

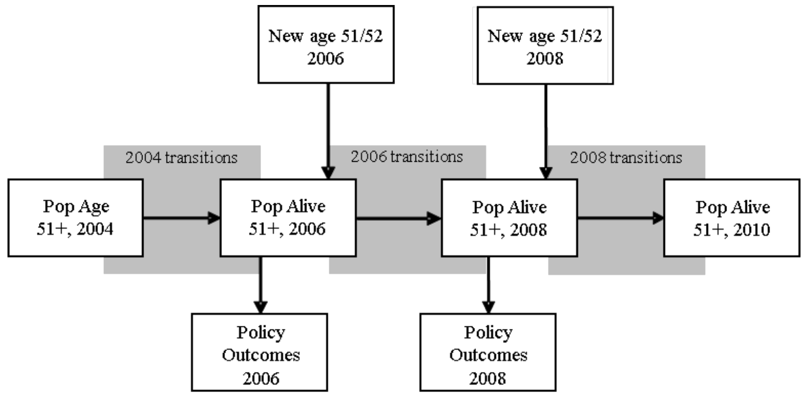

Figure 1: Architecture of the FEM

1.3 Comparison with other prominent microsimulation models of health expenditures

The FEM is unique among existing models that make health expenditure projections. It is the only model that projects health trends rather than health expenditures. It is also the only model that generates mortality out of assumptions on health trends rather than historical time series.

1.3.1 CBOLT Model

The Congressional Budget Office (CBO) uses time-series techniques to project health expenditure growth in the short term and then makes an assumption on long-term growth. They use a long term growth of excess costs of 2.3 percentage points starting in 2020 for Medicare. They then assume a reduction in excess cost growth in Medicare of 1.5% through 2083, leaving a rate of 0.9% in 2083. For non-Medicare spending they assume an annual decline of 4.5%, leading to an excess growth rate in 2083 of 0.1%.

1.3.2 Centers for Medicare and Medicaid Services

The Centers for Medicare and Medicaid Services (CMS) performs an extrapolation of medical expenditures over the first ten years, then computes a general equilibrium model for years 25 through 75 and linearly interpolates to identify medical expenditures in years 11 through 24 of their estimation. The core assumption they use is that excess growth of health expenditures will be one percentage point higher per year for years 25-75 (that is if nominal GDP growth is 4%, health care expenditure growth will be 5%).

2 Data sources used for estimation

The Health and Retirement Study is the main data source for the model.

Estimated Outcomes in Initial Conditions Model

Economic Outcomes	Health Outcomes
Employment	Hypertension
Earnings	Heart Disease
Wealth	Self-Reported Health
Defined Contribution Pension Wealth	BMI Status
Pension Plan Type	Smoking Status
AIME	Functional Status
Social Security Quarters of Coverage	
Health Insurance	

Estimated Outcomes in/from Transition Model

Economic Outcomes	Health Outcomes	Other Outcomes
Employment	Death	Income Tax Revenue
Earnings	Heart	Social Security Revenue
Wealth	Stroke	Medicare Revenue
Demographics	Cancer	Medical Expenses
Health Insurance	Hypertension	Medicare Part A Expenses
Disability Insurance Claim	Diabetes	Medicare Part B Expenses
Defined Benefit Claim	Lung Disease	Medicare Part B Enrollment
SSI Claim	Nursing Home	Medicare Part D Enrollment
Social Security Claim	BMI	OASI Enrollment
	Smoking Status	DI enrollment
	ADL Limitations	SSI enrollment
	IADL Limitations	Medicaid Enrollment
		Medicaid Expenditures

2.1 Health and Retirement Study

The Health and Retirement Study (HRS) waves 1998-2018 are used to estimate the transition model. Interviews occur every two years. We use the dataset created by RAND (RAND HRS, version K) as our basis for the analysis. We use all cohorts in the analysis and consider sampling weights whenever appropriate. When appropriately weighted, the HRS in 2016 is representative of U.S. households where at least one member is at least 51. The HRS is also used as the host data for the simulation (pop 51+ in 2016) and for new cohorts (aged 51 and 52 in 2016), when applicable.

The HRS adds new cohorts every six years. Until recently, the latest available cohort had been added in 2016, which is why that is the FEM's base year.

3 Data sources for trends and baseline scenario

3.1 Data for growth in wages

Wages are adjusted for real wage growth using historical real wage differential data until 2020 (the start of the pandemic). For post-2020 earnings, intermediate projections are used (SSA 2021 Trustees Report, table V.B1).

3.2 Demographic adjustments

We make adjustments to the weighting in the HRS to match population counts. Since we deleted some cases from the data and only considered the set of respondents with matched Social Security records, this takes account of selectivity based on these characteristics. We post-stratify the HRS sample by 5 year age groups, gender and race and rebalance weights using the 2016 American Community Survey estimates.

4 Estimation

In this section we describe the approach used to estimate the transition model, the core of the FEM, and the initial cohort model which is used to rejuvenate the simulation population.

4.1 Transition model

We consider a large set of outcomes for which we model transitions. Table 3 gives the set of outcomes considered for the transition model along with descriptive statistics and the population at risk when estimating the relationships.

Since we have a stock sample from the age 51+ population, each respondent goes through an individual-specific series of intervals. Hence, we have an unbalanced panel over the age range starting from 51 years old. Denote by j_{i0} the first age at which respondent i is observed and j_{iT_i} the last age when he is observed. Hence we observe outcomes at ages $j_i = j_{i0}, \ldots, j_{iT_i}$.

We first start with discrete outcomes which are absorbing states (e.g. disease diagnostic, mortality, benefit claiming). Record as $h_{i,j_i,m} = 1$ if the individual outcome m has occurred as of age j_i. We assume the individual-specific component of the hazard can be decomposed in a time invariant and variant part. The time invariant part is composed of the effect of observed characteristics x_i that are constant over the entire life course and initial conditions $h_{i,j_0,-m}$ (outcomes other than the outcome m) that are determined before the first age in which each individual is observed [1]. The time-varying part is the effect of previously diagnosed outcomes $h_{i,j_i-1,-m}$, on the hazard for m.[2] We assume an index of the form $z_{m,j_i} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + h_{i,j_0,-m}\psi_m$. Hence, the latent component of the hazard is modeled as

$$h^*_{i,j_i,m} = x_i\beta_m + h_{i,j_i-1,-m}\gamma_m + h_{i,j_0,-m}\psi_m + a_{m,j_i} + \varepsilon_{i,j_i,m}, \tag{1}$$

$$m = 1, \ldots, M_0,\ j_i = j_{i0}, \ldots, j_{i,T_i},\ i = 1, \ldots, N$$

The term $\varepsilon_{i,j_i,m}$ is a time-varying shock specific to age j_i. We assume that this last shock is normally distributed and uncorrelated across diseases. We approximate a_{m,j_i} with an age spline. After several

[1] Section **??** explains why the $h_{i,j_0,-m}$ terms are included.

[2] With some abuse of notation, $j_i - 1$ denotes the previous age at which the respondent was observed.

specification checks, knots at age 65 and 75 appear to provide the best fit. This simplification is made for computational reasons since the joint estimation with unrestricted age fixed effects for each condition would imply a large number of parameters. The absorbing outcome, conditional on being at risk, is defined as

$$h_{i,j_i,m} = \max\{I(h^*_{i,j_i,m} > 0), h_{i,j_i-1,m}\}$$

The occurrence of mortality censors observation of other outcomes in a current year. Mortality is recorded from exit interviews.

A number of restrictions are placed on the way feedback is allowed in the model. Table 4 documents restrictions placed on the transition model. We also include a set of other controls. A list of such controls is given in Table 5 along with descriptive statistics.

We have three other types of outcomes:

1. First, we have binary outcomes which are not an absorbing state, such as living in a nursing home. We specify latent indices as in (1) for these outcomes as well but where the lag dependent outcome also appears as a right-hand side variable. This allows for state-dependence.

2. Second, we have ordered outcomes. These outcomes are also modeled as in (1) recognizing the observation rule is a function of unknown thresholds ς_m. Similarly to binary outcomes, we allow for state-dependence by including the lagged outcome on the right-hand side.

3. The third type of outcomes we consider are censored outcomes, earnings and financial wealth. Earnings are only observed when individuals work. For wealth, there are a non-negligible number of observations with zero and negative wealth. For these, we consider two part models where the latent variable is specified as in (1) but model probabilities only when censoring does not occur. In total, we have M outcomes.

The parameters $\theta_1 = \left(\{\beta_m, \gamma_m, \psi_m, \varsigma_m\}_{m=1}^{M},\right)$, can be estimated by maximum likelihood. Given the normality distribution assumption on the time-varying unobservable, the joint probability of all time-intervals until failure, right-censoring or death conditional on the initial conditions $h_{i,j_0,-m}$ is the product of normal univariate probabilities. Since these sequences, conditional on initial conditions, are also independent across diseases, the joint probability over all disease-specific sequences is simply the product of those probabilities.

For a given respondent observed from initial age j_{i0} to a last age j_{T_i}, the probability of the observed health history is (omitting the conditioning on covariates for notational simplicity)

$$l_i^{-0}(\theta; h_{i,j_{i0}}) = \left[\prod_{m=1}^{M-1} \prod_{j=j_{i1}}^{j_{T_i}} P_{ij,m}(\theta)^{(1-h_{ij-1,m})(1-h_{ij,M})}\right] \times \left[\prod_{j=j_{i1}}^{j_{T_i}} P_{ij,M}(\theta)\right]$$

We use the -0 superscript to make explicit the conditioning on $\mathbf{h}_{i,j_{i0}} = (h_{i,j_{i0},0}, \ldots, h_{i,j_{i0},M})'$. We have limited information on outcomes prior to this age. The likelihood is a product of M terms with the mth term containing only $(\beta_m, \gamma_m, \psi_m, \varsigma_m)$. This allows the estimation to be done separately for each outcome.

4.1.1 Inverse Hyperbolic Sine Transformation

One problem fitting the wealth and earnings distribution is that they have a long right tail and wealth has some negative values. We use a generalization of the inverse hyperbolic sine transform

(IHT) presented in MacKinnon and Magee (1990). First denote the variable of interest y. The hyperbolic sine transform is

$$y = \sinh(x) = \frac{\exp(x) - \exp(-x)}{2} \tag{2}$$

The inverse of the hyperbolic sine transform is

$$x = \sinh^{-1}(y) = h(y) = \log(y + (1 + y^2)^{1/2})$$

Consider the inverse transformation. We can generalize such transformation, first allowing for a shape parameter θ,

$$r(y) = h(\theta y)/\theta \tag{3}$$

Such that we can specify the regression model as

$$r(y) = x\beta + \varepsilon, \varepsilon \sim \mathrm{N}(0, \sigma^2) \tag{4}$$

A further generalization is to introduce a location parameter ω such that the new transformation becomes

$$g(y) = \frac{h(\theta(y + \omega)) - h(\theta\omega)}{\theta h'(\theta\omega)} \tag{5}$$

where $h'(a) = (1 + a^2)^{-1/2}$.

We specify (4) in terms of the transformation g. The shape parameters can be estimated from the concentrated likelihood for θ, ω. We can then retrieve β, σ by standard OLS.

Upon estimation, we can simulate

$$\tilde{g} = x\hat{\beta} + \sigma\tilde{\eta}$$

where η is a standard normal draw. Given this draw, we can retransform using (5) and (2)

$$h(\theta(y + \omega)) = \theta h'(\theta\omega)\tilde{g} + h(\theta\omega)$$
$$\tilde{y} = \frac{\sinh\left[\theta h'(\theta\omega)\tilde{g} + h(\theta\omega)\right] - \theta\omega}{\theta}$$

5 Government revenues and expenditures

This gives a limited overview of how revenues and expenditures of the government are computed. These functions are based on 2016 rules, but we include predicted changes in program rules such changes based on year of birth (e.g. Normal retirement age).

We cover the following revenues and expenditures:

Revenues	**Expenditures**
Federal Income Tax	Social Security Retirement benefits
State and City Income Taxes	Social Security Disability benefits
Social Security Payroll Tax	Supplementary Security Income (SSI)
Medicare Payroll Tax	Medical Care Costs
Property Tax	Medicaid
	Medicare (parts A, B, and D)

5.1 Social Security benefits

Workers with 40 quarters of coverage and of age 62 are eligible to receive their retirement benefit. The benefit is calculated based on the Average Indexed Monthly Earnings (AIME) and the age at which benefits are first received. If an individual claims at their normal retirement age (NRA) (65 for those born prior to 1943, 66 for those between 1943 and 1957, and 67 thereafter), they receive their Primary Insurance Amount (PIA) as a monthly benefit. The PIA is a piece-wise linear function of the AIME. If a worker claims prior to their NRA, their benefit is lower than their PIA. If they retire after the NRA, their benefit is higher. While receiving benefits, earnings are taxed above a certain earning disregard level prior to the NRA. An individual is eligible to half of their spouse's PIA, properly adjusted for the claiming age, if that is higher than their own retirement benefit. A surviving spouse is eligible to the deceased spouse's PIA. Since we assume prices are constant in our simulations, we do not adjust benefits for the COLA (Cost of Living Adjustment) which usually follows inflation. We however adjust the PIA bend points for increases in real wages.

5.2 Disability Insurance benefits

Workers with enough quarters of coverage and under the normal retirement age are eligible for their PIA (no reduction factor) if they are judged disabled (which we take as the predicted outcome of DI receipt) and earnings are under a cap called the Substantial Gainful Activity (SGA) limit. This limit was $13,560 in 2016. We ignore the 9 month trial period over a 5 year window in which the SGA is ignored.

6 Implementation

The FEM is implemented in multiple parts. Estimation of the transition and cross sectional models is performed in Stata. The incoming cohort model is estimated in Stata using the CMP package (Roodman, 2011). The simulation is implemented in C++ to increase speed.

To match the two year structure of the Health and Retirement Study (HRS) data used to estimate the transition models, the FEM simulation proceeds in two year increments. The end of each two year step is designed to occur on July 1st to allow for easier matching to population forecasts from Social Security. A simulation of the FEM proceeds by first loading a population representative of the age 51+ US population in 2016, generated from HRS. In two year increments, the FEM applies the transition models for mortality, health, working, wealth, earnings, and benefit claiming with Monte Carlo decisions to calculate the new states of the population. The population is also adjusted by immigration forecasts from the US Census Department, stratified by race and age. If incoming cohorts are being used, the new 51/52 year olds are added to the population. The number of new 51/52 year olds added is consistent with estimates from the Census, stratified by race. Once the new states have been determined and new 51/52 year olds added, the cross sectional models for medical costs, and calculations for government expenditures and revenues are performed. Summary variables are then computed. Computation of medical costs includes the persons that died to account for end of life costs. Other computations, such as Social Security benefits and government tax revenues, are restricted to persons alive at the end of each two year interval. To eliminate uncertainty due to the Monte Carlo decision rules, the simulation is performed multiple times (here 75), and the mean of each summary variable is calculated across repetitions.

FEM simulation takes as inputs assumptions regarding growth in the national wage index, normal retirement age, real medical cost growth, interest rates, cost of living adjustments, the consumer price index, significant gainful activity, and deferred retirement credit. The default assumptions are taken from the 2010 Social Security Intermediate scenario, adjusted for no price increases after 2010. Therefore simulation results are in real 2009 dollars. Table 10 shows assumptions for each birth year.

Different simulation scenarios are implemented by changing any of the following components: incoming cohort model, transition models, interventions that adjust the probabilities of specific transition, and changes to assumptions on future economic conditions.

7 Validation

We perform two validation exercises:

1. Cross-validation
2. External corroboration

Cross-validation is a test of the simulations internal validity that compares simulated outcomes to actual outcomes, and external corroboration compares model forecasts to others' forecasts.

7.1 Cross-validation

The cross-validation exercise randomly samples half of the HRS respondent IDs for use in estimating the transition models. The respondents not used for estimation, but who were present in the HRS sample in 1998, are then simulated from 1998 through 2018. Demographic and health outcomes are compared between the simulated ("FEM") and actual ("HRS") cohorts. These results are presented in Table 6 - Table 9 for 2000, 2006, 2012, and 2018 with a statistical test of the difference between the average values in the two cohorts.

Worth noting is how the composition of the cohort changes in this exercise. In 1998, the sample represents those 51 and older. Since we follow a fixed cohort, the average age of the cohort will increase 71 and older in 2018. This has consequences for some measures in later years where the eligible cohort shrinks.

7.1.1 Demographics

Demographic measures are presented in Table 7. Demographic differences between the two cohorts are small. The gender balance and fraction of the cohort that is non-Hispanic Black or Hispanic is consistent.

7.1.2 Health Outcomes

The two cohorts are not statistically different from each other for prevalence of most health outcomes in each of the examined years until 2018. In 2018, the prevalence rates of cancer, diabetes, and heart disease were not statistically different between the FEM and HRS cohorts. Hypertension, lung disease, and stroke prevalence were approximately 2.5 percentage points higher, and the prevalence rates of having any ADLs and of any IADLs were approximately 3.5 percentage points higher in the FEM cohort than in the HRS cohort.

7.1.3 Health Risk Factors

Average BMI is slightly lower for the FEM cohort in 2018 (27.3 for the FEM vs. 27.8 for the HRS). In terms of practical significance, this difference is equivalent to fewer than four pounds for an individual who is 58. Current smoking prevalence is slightly higher in the FEM cohort than in the HRS cohort, whereas the prevalence of ever-smokers is the same between the two cohorts

On the whole, the cross-validation exercise is reassuring. Comparing simulated outcomes to actual outcomes using a set of transition models estimated on a separate population reveals that the majority of outcomes of interest are not statistically different. In cases where they are, the practical difference is potentially low.

7.2 External Corroboration

Finally, we compare FEM population forecasts to Census forecasts of the US population. Here, we focus on the full HRS population (51 and older) and those 65 and older. For this exercise, we begin the simulation in 2010 and simulate the full population through 2050. Population projections are compared to the 2012 Census projections for years 2012 through 2050. FEM population forecasts are always within two percent of Census forecasts.

8 Baseline Forecasts

In this section we present baseline forecasts of the Future Elderly Model. The figures show data from the HRS for the 55+ population from 1998 through 2018 and forecasts from the FEM for the 55+ population beginning in 2010.

8.1 Disease Prevalence

Figure 2 depicts the six chronic conditions we project for men. And Figure 3 depicts the historic and forecasted values for women.

Figure 4 shows historic and forecasted levels for any ADL difficulties, three or more ADL difficulties, any IADL difficulties, and two or more IADL difficulties for men 55 and older. Figure 5 shows historic and forecasted levels for any ADL difficulties, three or more ADL difficulties, any IADL difficulties, and two or more IADL difficulties for women 55 and older.

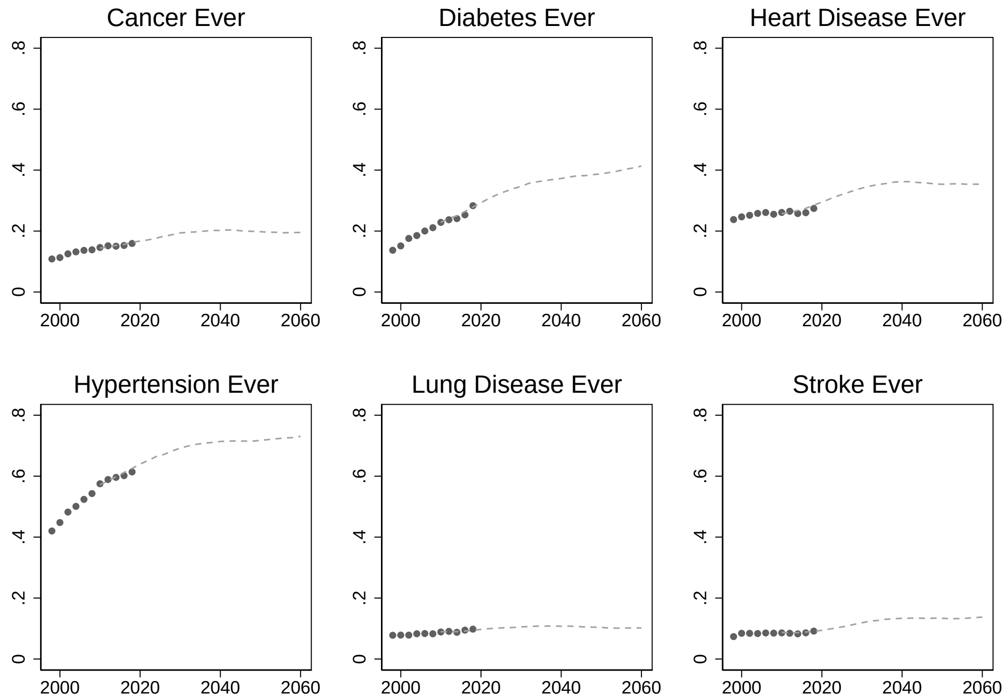

Figure 2: Historic and Forecasted Chronic Disease Prevalence for Men 55+

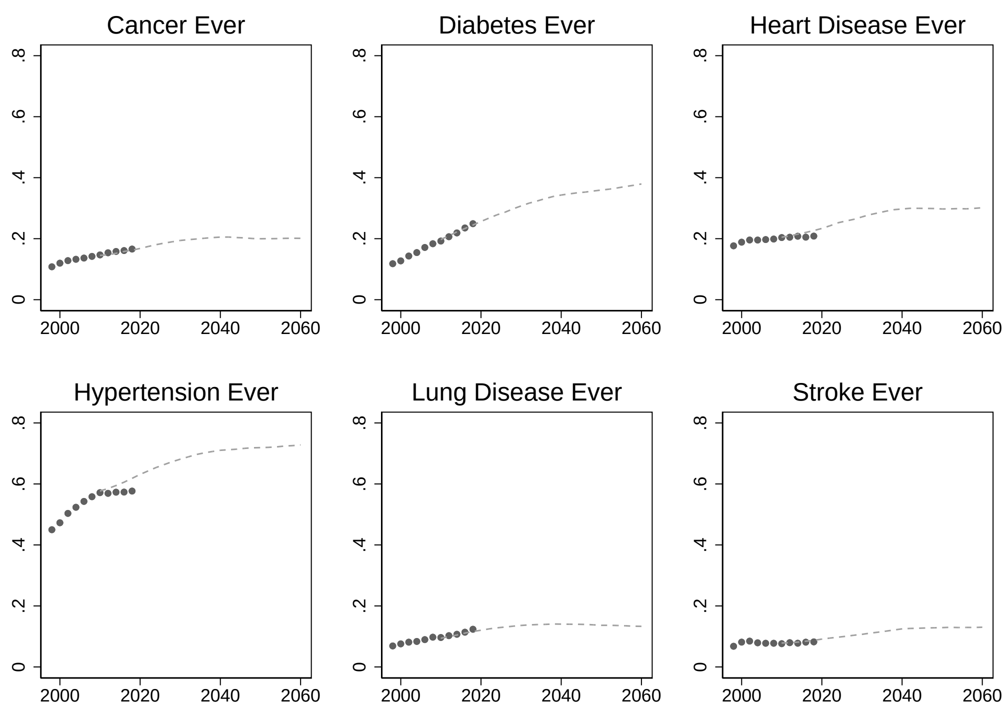

Figure 3: Historic and Forecasted Chronic Disease Prevalence for Women 55+

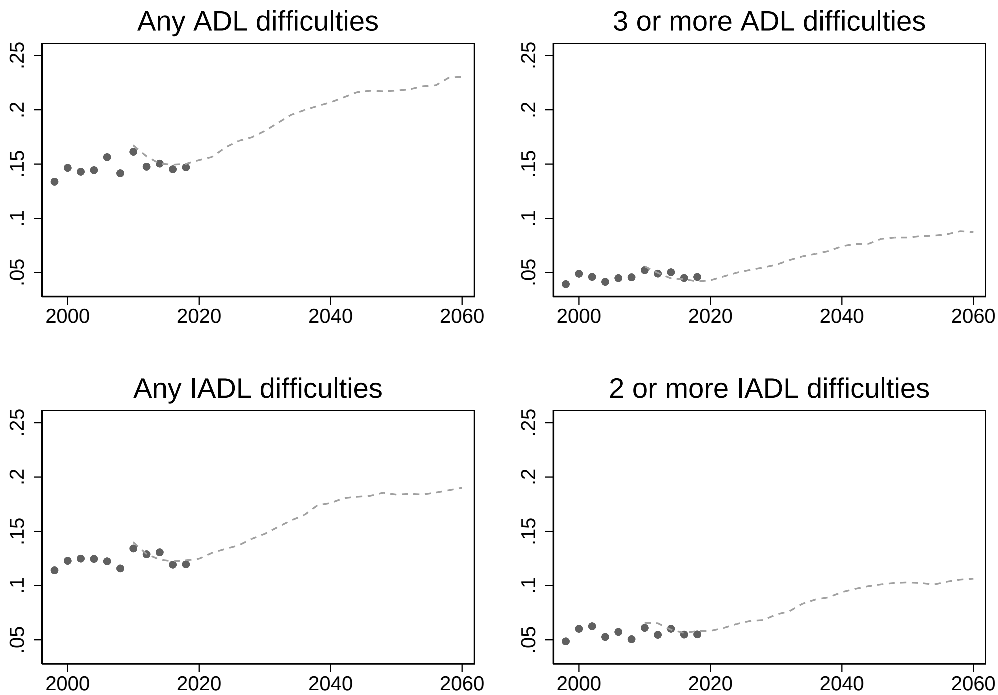

Figure 4: Historic and Forecasted ADL and IADL Prevalence for Men 55+

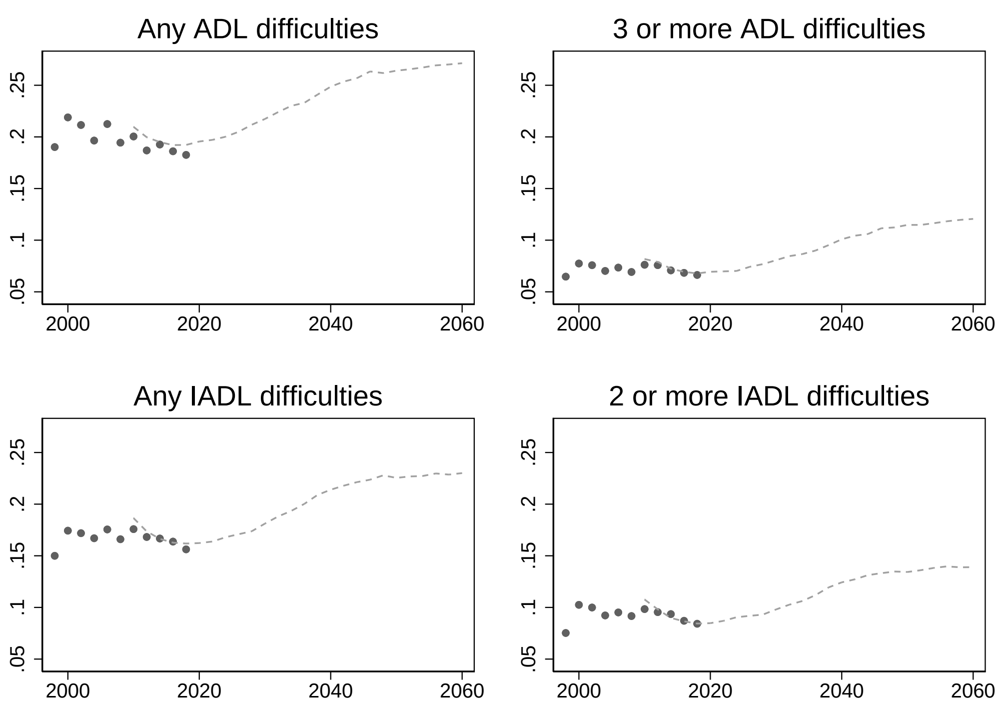

Figure 5: Historic and Forecasted ADL and IADL Prevalence for Women 55+

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10 Tables

	Prevalence %							
Source (years, ages)	Cancer	Heart Diseases	Stroke	Diabetes	Hypertension	Lung Disease	Overweight	Obese
HRS (1991-2008, 55-64)	9%	14%	4%	17%	45%	7%	38%	34%
NHIS (1997-2010, 55-64)	8%	17%	4%	14%	44%	8%	37%	33%
MEPS (2000-2010, 55-64)	7%	17%	4%	15%	47%	7%	38%	32%
HRS (1991-2008, 65+)	18%	30%	10%	21%	60%	11%	38%	25%
NHIS (1997-2010, 65+)	16%	31%	9%	17%	56%	10%	36%	25%
MCBS (2000-2010, 65+)	18%	40%	11%	23%	65%	16%	38%	23%
MEPS (2000-2010, 65+)	12%	33%	11%	19%	64%	10%	38%	25%

Table 1: Health condition prevalences in survey data

	Survey			
Disease	HRS	NHIS	MEPS	MCBS
Cancer	Has a doctor ever told you that you have cancer or a malignant tumor, excluding minor skin cancers?	Have you ever been told be a doctor or other health professional that you had cancer or a malignanacy of any kind? (WHEN RECODED, SKIN CANCERS WERE EXCLUDED)	List all the conditions that have bothered (the person) from (START time) to (END time) CCS codes for the conditions list are 11-21, 24-45	Has a doctor ever told you that you had any (other) kind of cancer malignancy, or tumor other than skin cancer?
Heart Diseases	Has a doctor ever told you that you had a heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems?	Four separate questions were asked about whether ever told by a docotor or oither health professional that had: CHD, Angina, MI, other heart problems.	Have you ever been told by a doctor or health professional that you have CHD; Angina; MI; other heart problems	Six separate questions were asked about whether ever told by a doctor that had: Angina or MI; CHD; other heart problems (included four questions)
Stroke	Has a doctor ever told you that you had a stroke?	Have you EVER been told by a doctor or other health professional that you had a stroke?	If Female, add: [Other than during pregnancy,] Have you ever been told by a doctor or health professional that you have a stroke or TIA (transient ischemic attack)	[Since (PREV< SUPP. RD. INT. DATE),] has a doctor (ever) told (you/SP) that (you/he/she) had a stroke, a brain hemorrhage, or a cerebrovascular accident?
Diabetes	Has a doctor ever told you that you have diabetes or high blood sugar?	If Female, add: [Other than during pregnancy,] Have you ever been told by a doctor or health professional that you have diabetes or sugar diabetes?	If Female, add: [Other than during pregnancy,] Have you hever been told by a doctor or health professional that you have diabetes or sugar diabetes?	Has a doctor (ever) told (you/SP) that (you/he/she) had diabetes, high blood sugar, or sugar in (your/his/her) urine? [DO NOT INCLUDE BOERDERLINE PREGNANCY, OR PREDIABETEIC DIABETES.]
Hypertension	Has a doctor ver told you that you have high blood pressure or hypertension?	Have you EVER been told by a doctor or other health professional that you had Hypertension, also called high blood pressure?	Have you EVER been told by a doctor or other health professional that you had Hypertension, also called high blood pressure?	Has a doctor (ever) told (you/SP) that (you/he/she) (still) (had) (have/has) hypertension, sometimes called high blood pressure?
Lung Disease	Has a doctor ever told you that you have chronic lung disease such a schronic bronchitis or emphysema? [IWER: DO NOT INCLUDE ASTHMA]	Question 1: During the PAST 12 MONTHS, have you ever been told by a doctor or other health professional that you had chronic bronchitis? Question 2: Have you EVER been told by a docotor or other health professional that you had emphysema?	List all the conditions that have bothered (the person) from (START time) to (END time) CCS codes for the conditions list are 127, 129-312	Has a doctor (ever) told (you/SP) that (you/he/she) had emphysema, asthma, or COPD? [COPD=CHRONIC OBSTRUCTIVE PULMONARY DISEASE.]
Overweight	Self-reported body weight and height			
Obese				

Table 2: Survey questions used to determine health conditions

			Type	At risk	Mean/fraction
Disease	heart disease		biennial incidence	undiagnosed	0.03
	hypertension		biennial incidence	undiagnosed	0.04
	stroke		biennial incidence	undiagnosed	0.01
	lung disease		biennial incidence	undiagnosed	0.01
	cancer		biennial incidence	undiagnosed	0.02
	diabetes		biennial incidence	undiagnosed	0.02
Risk Factors	Smoking Status	never smoked	ordered	all	0.43
		ex smoker	ordered	all	0.43
		current smoker	ordered	all	0.14
	Log BMI		continuous	all	3.31
	ADL Status	no ADLs	ordered	all	0.76
		1 ADL	ordered	all	0.08
		2 ADLS	ordered	all	0.04
		3+ ADLS	ordered	all	0.07
	IADL Status	no IADLs	ordered	all	0.78
		1 IADL	ordered	all	0.07
		2+ IADLs	ordered	all	0.09
LFP & Benefits	working		prevalence	age < 80	0.47
	DB pension receipt		biennial incidence	eligible & not receiving	0.11
	SS benefit receipt		biennial incidence	eligible & not receiving	0.07
	DI benefit receipt		prevalence	eligible & age < 65	0.04
	Any health insurance		prevalence	age < 65	0.87
	SSI receipt		prevalence	all	0.03
	Nursing Home residency		prevalence	all	0.02
	Death		biennial incidence	all	0.07
Financial Resources ($USD 2004)	financial wealth		median	all non-zero wealth	186,156.17
	earnings		median	all working	2,849.16
	wealth positive		prevalence	all	0.96

Table 3: Outcomes in the transition model. Estimation sample is HRS 1991-2008 waves.

Value at time $T-1$	Outcome at time T																			
	Heart disease	hypertension	stroke	Lung disease	diabetes	cancer	disability	mortality	Smoking status	BMI	Any HI	DI Claim	SS Claim	DB Claim	SSI Claim	Nursing Home	Work	Earnings	Nonzero Wealth	Wealth
Heart disease			✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Blood pressure	✓		✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Stroke							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lung disease							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Diabetes	✓	✓	✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cancer			✓				✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Disability							✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Claimed DI											✓	✓	✓	✓	✓		✓	✓	✓	✓
Claimed SS											✓			✓	✓		✓	✓	✓	✓
Claimed DB													✓		✓		✓	✓	✓	✓
Claimed SSI															✓					
Work											✓	✓	✓		✓		✓	✓	✓	✓
Earnings											✓	✓	✓	✓	✓		✓	✓	✓	✓
Nonzero wealth											✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wealth											✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nursing home stay															✓	✓			✓	✓

Table 4: Restrictions on transition model. ✓indicates that an outcome at time $T-1$ is allowed in the transition model for an outcome at time T.

	Unweighted Statistics			
Control variable	Mean	Standard deviation	Minimum	Maximum
Non-Hispanic Black	0.138	0.345	0	1
Hispanic	0.0887	0.284	0	1
Less than high school	0.251	0.433	0	1
Some college and above	0.397	0.489	0	1
Male	0.436	0.496	0	1
Ever smoked	0.590	0.492	0	1
Fitted values	1866	1114	-96.92	4356
frq				
Init.of Any DB from current job	0.173	0.378	0	1
fnra3	0.0723	0.259	0	1
fnra4	0.0450	0.207	0	1
fnra5	0.0965	0.295	0	1
Any DC from current job	0.109	0.312	0	1
(IHT of DC wlth in 1000s)/100 if any DC, zero otherwise	0.000148	0.00254	0	0.0696

Table 5: Desciptive statistics for exogeneous control variables in 2004 HRS ages 51+ sample used as simulation stock population

	2000			2006			2012			2018		
	FEM	HRS		FEM	HRS		FEM	HRS		FEM	HRS	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p	mean	mean	p
Died	0.058	0.050	0.007	0.069	0.074	0.224	0.091	0.083	0.045	0.113	0.106	0.208
Lives in nursing home	0.029	0.018	0.000	0.038	0.025	0.000	0.052	0.036	0.000	0.075	0.046	0.000

Table 6: Crossvalidation of 1998 cohort: Simulated vs reported mortality and nursing home outcomes in 2000, 2006, 2012, and 2018

	2000			2006			2012			2018		
	FEM	HRS		FEM	HRS		FEM	HRS		FEM	HRS	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p	mean	mean	p
Age on July 1st	66.676	65.991	0.000	70.699	70.184	0.000	74.572	74.573	0.992	78.450	78.537	0.539
Black	0.087	0.083	0.268	0.086	0.079	0.124	0.085	0.077	0.089	0.084	0.076	0.231
Hispanic	0.061	0.057	0.151	0.064	0.059	0.112	0.069	0.062	0.096	0.073	0.063	0.085
Male	0.456	0.449	0.332	0.449	0.445	0.670	0.438	0.430	0.368	0.428	0.425	0.798

Table 7: Crossvalidation of 1998 cohort: Simulated vs reported demographic outcomes in 2000, 2006, 2012, and 2018

	2000			2006			2012			2018		
	FEM	HRS		FEM	HRS		FEM	HRS		FEM	HRS	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p	mean	mean	p
Any ADLs	0.154	0.163	0.072	0.170	0.185	0.009	0.202	0.192	0.198	0.251	0.214	0.000
Any IADLs	0.128	0.121	0.121	0.145	0.145	0.931	0.177	0.176	0.861	0.226	0.193	0.000
Cancer	0.118	0.119	0.784	0.169	0.162	0.243	0.216	0.216	0.999	0.259	0.258	0.930
Diabetes	0.143	0.139	0.393	0.202	0.198	0.567	0.252	0.244	0.289	0.302	0.291	0.313
Heart Disease	0.200	0.197	0.675	0.258	0.260	0.750	0.323	0.324	0.841	0.395	0.388	0.571
Hypertension	0.452	0.443	0.175	0.567	0.568	0.924	0.660	0.661	0.897	0.733	0.711	0.041
Lung Disease	0.073	0.073	0.907	0.100	0.099	0.866	0.127	0.120	0.257	0.149	0.129	0.013
Stroke	0.066	0.065	0.891	0.090	0.088	0.692	0.115	0.114	0.808	0.148	0.122	0.001

Table 8: Crossvalidation of 1998 cohort: Simulated vs reported binary health outcomes in 2000, 2006, 2012, and 2018

	2000			2006			2012			2018		
	FEM	HRS		FEM	HRS		FEM	HRS		FEM	HRS	
Outcome	mean	mean	p	mean	mean	p	mean	mean	p	mean	mean	p
BMI	27.078	27.289	0.004	27.354	27.894	0.000	27.482	27.831	0.001	27.411	27.884	0.000
Current smoker	0.148	0.159	0.021	0.127	0.123	0.426	0.109	0.089	0.000	0.091	0.055	0.000
Ever smoked	0.593	0.603	0.144	0.583	0.593	0.205	0.568	0.575	0.420	0.550	0.549	0.892

Table 9: Crossvalidation of 1998 cohort: Simulated vs reported risk factor outcomes in 2000, 2006, 2012, and 2018

Birth year	Normal Retirement Age	Delayed Retirement Credit
1890	780	.03
1891	780	.03
1892	780	.03
1893	780	.03
1894	780	.03
1895	780	.03
1896	780	.03
1897	780	.03
1898	780	.03
1899	780	.03
1900	780	.03
1901	780	.03
1902	780	.03
1903	780	.03
1904	780	.03
1905	780	.03
1906	780	.03
1907	780	.03
1908	780	.03
1909	780	.03
1910	780	.03
1911	780	.03
1912	780	.03
1913	780	.03
1914	780	.03
1915	780	.03
1916	780	.03
1917	780	.03
1918	780	.03
1919	780	.03
1920	780	.03
1921	780	.03
1922	780	.03
1923	780	.03
1924	780	.03
1925	780	.035
1926	780	.035
1927	780	.04
1928	780	.04
1929	780	.045
1930	780	.045
1931	780	.05
1932	780	.05
1933	780	.055
1934	780	.055
1935	780	.06
1936	780	.06
1937	780	.065
1938	782	.065
1939	784	.07
1940	786	.07
1941	788	.075
1942	790	.075
1943	792	.08
1944	792	.08
1945	792	.08
1946	792	.08
1947	792	.08
1948	792	.08
1949	792	.08
1950	792	.08
1951	792	.08
1952	792	.08
1953	792	.08
1954	792	.08
1955	794	.08
1956	796	.08
1957	798	.08
1958	800	.08
1959	802	.08
1960	804	.08

Table 10: Assumptions for each birth year. In years after 1960, all values are held constant at their 1960 levels.

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MacKinnon, J. G. and Magee, L. (1990). Transforming the dependent variable in regression models. *International Economic Review*, pages 315–339.

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This file provides supplementary details for the paper:
Title: The Effect of US COVID-19 Excess Mortality on Social Security Outlays
Authors: Hanke Heun-Johnson, Darius Lakdawalla, Julian Reif, and Bryan Tysinger

The following sheets contain transition model estimates for relevant variables in the Future Elderly Model, for population ages 55 and over in 2020.

Binaries
This worksheet reports estimates of the probability of dying, of developing a chronic condition (stroke, heart disease, cancer, hypertension diabetes, lung disease, and congestive heart failure), of having a heart attack, of living in a nursing home, of claiming SSDI, claiming OASI, and working for pay

Ordered Probits
This worksheet reports estimates of the probability of changing smoking status, changing ADL and IADL status, and cognitive status

OLS
This worksheet reports estimates of how BMI is updated in the microsimulation.

MiCDA (enclave)
Joint estimation model coefficients for AIME and quarters worked
a. 50+ yrs, with non-missing earnings and quarters worked, reporting non-zero OASI income
b. 50+ yrs, with non-missing earnings and quarters worked, reporting zero OASI income
c. 50-55 yrs, with non-missing earnings and quarters worked
Model for whether a person worked any quarters. 50+ yrs, with non-missing earnings and quarters worked

	Died (died)		Died (died)		Heart disease		Heart disease		Stroke (stroke)		Stroke (stroke)	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	0.010	0.022	0.001		-0.079***	0.025	-0.006		0.080***	0.030	0.003	
Hispanic	-0.155***	0.031	-0.010		-0.118***	0.032	-0.008		-0.065	0.042	-0.002	
Less than high school	0.025	0.020	0.002		0.044*	0.024	0.004		0.038	0.030	0.001	
Some college and above	-0.064***	0.019	-0.005		-0.060***	0.021	-0.005		-0.033	0.026	-0.001	
Male	-0.449	0.358	-0.030		0.158***	0.025	0.013		0.047	0.032	0.002	
Male AND Less than high school	-0.001	0.030	-0.000		-0.050	0.038	-0.004		0.053	0.046	0.002	
Male AND Non-Hispanic Black	0.054	0.033	0.004		-0.138***	0.040	-0.010		-0.030	0.047	-0.001	
Male AND Hispanic	0.079*	0.045	0.006		-0.070	0.048	-0.005		0.019	0.062	0.001	
Male AND Some college and above	-0.016	0.028	-0.001		0.038	0.031	0.003		0.032	0.040	0.001	
Min(63, two-year lag of age)	0.022***	0.004	0.002		0.018***	0.003	0.001		0.018***	0.004	0.001	
Min(Max(0, two-year lag age - 63), 73 - 63)	0.029***	0.003	0.002		0.021***	0.002	0.002		0.020***	0.003	0.001	
Min(Max(0, two-year lag age - 73), 83 - 73)	0.041***	0.003	0.003									
Max(0, two-year lag age - 83)	0.057***	0.003	0.004									
Two-year lag of Heart disease	0.131***	0.021	0.010						0.189***	0.020	0.008	
Two-year lag of Stroke	0.171***	0.022	0.014									
Two-year lag of Cancer	0.402***	0.020	0.037						-0.029	0.026	-0.001	
Two-year lag of Hypertension	0.086***	0.018	0.006		0.192***	0.014	0.015		0.147***	0.019	0.005	
Two-year lag of Diabetes	0.163***	0.020	0.013		0.119***	0.019	0.010		0.120***	0.023	0.005	
Two-year lag of Lung disease	0.284***	0.022	0.025									
Two-year lag of R had heart attack since last wave	0.054	0.047	0.004						0.151***	0.053	0.006	
Two-year lag of Has exactly 1 IADL	0.267***	0.026	0.023									
Two-year lag of Has 2 or more IADLs	0.523***	0.026	0.055									
Two-year lag of Has exactly 1 ADL	0.161***	0.025	0.013									
Two-year lag of Has exactly 2 ADLs	0.214***	0.032	0.018									
Two-year lag of Has 3 or more ADLs	0.444***	0.028	0.045									
Two-year lag of Current smoking	0.277***	0.027	0.024		0.110***	0.023	0.009		0.209***	0.029	0.009	
Two-year lag of Widowed	0.048***	0.018	0.004		0.023	0.019	0.002		0.060***	0.023	0.002	
Heart problem status at age 50 (1/0)-imputed	-0.048	0.073	-0.003						0.244***	0.065	0.011	
Stroke status at age 50 (1/0)-imputed	-0.230**	0.104	-0.013		0.241**	0.094	0.023					
Cancer status at age 50 (1/0)-imputed	-0.147***	0.043	-0.009		0.138***	0.040	0.012		0.139***	0.054	0.006	
Diabetes status at age 50 (imputed)	0.073**	0.035	0.006		0.170***	0.031	0.015		0.116***	0.037	0.005	
Init. of Ever smoked	0.205***	0.020	0.014		0.042**	0.017	0.003		0.031	0.022	0.001	
Smoking status at age 50 (imputed)	-0.155***	0.024	-0.010		0.075***	0.020	0.006		-0.004	0.025	-0.000	
Two-year lag of Ever had congestive heart failure	0.255***	0.029	0.022									
male l2age65l	0.011*	0.006	0.001									
male l2age6574	0.000	0.005	0.000									
male l2age7584	-0.002	0.005	-0.000									
male l2age85p	0.011**	0.005	0.001									
Male AND Two-year lag of Ever had congestive heart failure	0.015	0.041	0.001									
Male AND Two-year lag of Heart disease	-0.047	0.029	-0.003									
Male AND Two-year lag of Stroke	-0.056*	0.033	-0.004									
Male AND Two-year lag of Cancer	-0.065**	0.029	-0.004									
Male AND Two-year lag of Hypertension	-0.011	0.025	-0.001									
Male AND Two-year lag of Diabetes	-0.019	0.029	-0.001									
Male AND Two-year lag of Lung disease	0.101***	0.033	0.008									
Male AND Two-year lag of R had heart attack since last wave	0.119*	0.064	0.009									
Male AND Two-year lag of Has exactly 1 IADL	-0.078**	0.038	-0.005									
Male AND Two-year lag of Has 2 or more IADLs	-0.069*	0.040	-0.005									
Male AND Two-year lag of Has exactly 1 ADL	0.062*	0.037	0.005									
Male AND Two-year lag of Has exactly 2 ADLs	0.128***	0.049	0.010									
Male AND Two-year lag of Has 3 or more ADLs	0.123***	0.043	0.010									
Male AND Two-year lag of Current smoking	0.033	0.038	0.002									
Male AND Two-year lag of Widowed	0.026	0.032	0.002									
Male AND Heart problem status at age 50 (1/0)-imputed	0.147	0.094	0.012									
Male AND Stroke status at age 50 (1/0)-imputed	0.084	0.161	0.006									
Male AND Cancer status at age 50 (1/0)-imputed	0.067	0.087	0.005									
Male AND Diabetes status at age 50 (imputed)	0.041	0.052	0.003									
Male AND Init. of Ever smoked	-0.063**	0.030	-0.004									
Male AND Smoking status at age 50 (imputed)	0.098***	0.032	0.007									
Max(0, two-year lag age - 73)					0.017***	0.002	0.001		0.027***	0.002	0.001	
Splined two-year lag of BMI <= log(30)					-0.035	0.083	-0.003		-0.306***	0.099	-0.011	
Splined two-year lag of BMI > log(30)					0.287***	0.108	0.022		0.018	0.131	0.001	
Splined init of BMI age 50 <= log(30)					0.127	0.084	0.010		0.232**	0.102	0.008	
Splined init of BMI age 50 > log(30)					0.229**	0.114	0.018		0.339**	0.137	0.012	
Log of years between current interview and previous					0.264***	0.039	0.021		0.364***	0.050	0.013	
cons	-3.935***	0.237			-3.689***	0.255			-3.702***	0.336		

	Cancer (cancre)		Cancer (cancre)		Hypertension		Hypertension		Diabetes (diabe)		Diabetes (diabe)	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	-0.117***	0.030	-0.006		0.187***	0.027	0.033		0.129***	0.025	0.009	
Hispanic	-0.169***	0.041	-0.008		0.050*	0.030	0.008		0.318***	0.030	0.025	
Less than high school	-0.013	0.030	-0.001		0.110***	0.026	0.018		0.080***	0.027	0.005	
Some college and above	0.052**	0.024	0.003		-0.058***	0.020	-0.009		-0.028	0.022	-0.002	
Male	0.131***	0.027	0.007		0.000	0.025	0.000		0.089***	0.027	0.006	
Male AND Less than high school	0.051	0.043	0.003		-0.076*	0.040	-0.012		-0.046	0.041	-0.003	
Male AND Non-Hispanic Black	0.142***	0.043	0.009		0.042	0.042	0.007		0.020	0.040	0.001	
Male AND Hispanic	-0.043	0.058	-0.002		0.087*	0.045	0.015		-0.125***	0.046	-0.007	
Male AND Some college and above	-0.034	0.034	-0.002		0.001	0.031	0.000		0.024	0.034	0.001	
Min(63, two-year lag of age)	0.023***	0.003	0.001		0.010***	0.002	0.002		0.014***	0.002	0.001	
Min(Max(0, two-year lag age - 63), 73 - 63)	0.017***	0.003	0.001		0.007***	0.002	0.001		-0.004	0.003	-0.000	
Two-year lag of Diabetes					0.137***	0.024	0.023					
Two-year lag of Current smoking	0.071***	0.026	0.004		0.089***	0.023	0.015		-0.043*	0.026	-0.003	
Two-year lag of Widowed	-0.023	0.022	-0.001		0.088***	0.021	0.015		0.040*	0.022	0.003	
Heart problem status at age 50 (1/0)-imputed	0.074	0.065	0.004		0.074	0.070	0.012		0.169***	0.062	0.012	
Stroke status at age 50 (1/0)-imputed	0.032	0.115	0.002		-0.153	0.126	-0.022		0.079	0.094	0.005	
Cancer status at age 50 (1/0)-imputed					0.044	0.039	0.007		0.002	0.043	0.000	
Diabetes status at age 50 (imputed)	0.050	0.034	0.003		0.165***	0.038	0.029					
Init. of Ever smoked	0.086***	0.019	0.005		-0.011	0.017	-0.002		-0.032*	0.019	-0.002	
Smoking status at age 50 (imputed)	-0.002	0.022	-0.000		0.017	0.021	0.003		0.133***	0.022	0.009	
Max(0, two-year lag age - 73)	-0.002	0.002	-0.000		0.001	0.002	0.000		-0.007***	0.003	-0.000	
Splined two-year lag of BMI <= log(30)	-0.081	0.094	-0.004		0.576***	0.087	0.091		1.134***	0.105	0.070	
Splined two-year lag of BMI > log(30)	-0.078	0.127	-0.004		0.454***	0.133	0.072		1.166***	0.107	0.072	
Splined init of BMI age 50 <= log(30)	0.125	0.094	0.007		0.108	0.087	0.017		0.641***	0.100	0.040	
Splined init of BMI age 50 > log(30)	0.227*	0.134	0.012		-0.052	0.142	-0.008		-0.224*	0.117	-0.014	
Log of years between current interview and previous	0.324***	0.044	0.018		0.312***	0.039	0.050		0.349***	0.042	0.022	
cons	-3.913***	0.281			-4.492***	0.234			-8.923***	0.295		

	Lung disease		Lung disease		Claiming SSDI		Claiming SSDI		Claiming OASI		Claiming OASI	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	-0.069**	0.031	-0.002		0.099***	0.036	0.006		-0.137***	0.032	-0.051	
Hispanic	-0.109***	0.042	-0.003		-0.170***	0.049	-0.009		-0.166***	0.040	-0.061	
Less than high school	0.139***	0.030	0.005		-0.127***	0.042	-0.007		-0.063*	0.036	-0.024	
Some college and above	-0.047*	0.027	-0.002		-0.036	0.034	-0.002		-0.287***	0.028	-0.108	
Male	0.064**	0.031	0.002		0.224***	0.042	0.014		-0.132***	0.035	-0.050	
Male AND Less than high school	-0.094**	0.046	-0.003		0.131**	0.064	0.009		0.080	0.054	0.031	
Male AND Non-Hispanic Black	-0.034	0.049	-0.001		-0.074	0.054	-0.004		0.082*	0.049	0.031	
Male AND Hispanic	-0.076	0.064	-0.002		-0.062	0.074	-0.004		0.075	0.059	0.029	
Male AND Some college and above	-0.102**	0.040	-0.003		-0.125**	0.052	-0.007		0.115***	0.041	0.044	
Min(63, two-year lag of age)	0.012***	0.003	0.000									
Min(Max(0, two-year lag age - 63), 73 - 63)	0.019***	0.003	0.001									
Two-year lag of Heart disease					0.109***	0.031	0.007		-0.046*	0.026	-0.017	
Two-year lag of Stroke					0.089*	0.047	0.006		-0.075*	0.041	-0.028	
Two-year lag of Cancer					0.113**	0.048	0.007		-0.032	0.034	-0.012	
Two-year lag of Hypertension					0.136***	0.025	0.008		0.065***	0.019	0.025	
Two-year lag of Diabetes					0.084**	0.034	0.005		-0.036	0.026	-0.014	
Two-year lag of Lung disease					0.118***	0.037	0.008		-0.071**	0.035	-0.027	
Two-year lag of Has exactly 1 IADL					0.260***	0.037	0.019		-0.048	0.040	-0.018	
Two-year lag of Has 2 or more IADLs					0.209***	0.045	0.015		0.020	0.050	0.007	
Two-year lag of Has exactly 1 ADL					0.327***	0.037	0.026		-0.067*	0.037	-0.025	
Two-year lag of Has exactly 2 ADLs					0.313***	0.049	0.025		-0.022	0.054	-0.008	
Two-year lag of Has 3 or more ADLs					0.462***	0.046	0.042		-0.122**	0.053	-0.045	
Two-year lag of Current smoking	0.334***	0.025	0.015									
Two-year lag of Widowed	0.036	0.024	0.001		0.062	0.045	0.004		0.149***	0.032	0.057	
Heart problem status at age 50 (1/0)-imputed	0.226***	0.067	0.010		0.099	0.081	0.006		-0.110	0.078	-0.040	
Stroke status at age 50 (1/0)-imputed	0.485***	0.088	0.028		-0.008	0.090	-0.000		-0.135	0.138	-0.050	
Cancer status at age 50 (1/0)-imputed	0.223***	0.045	0.009		0.005	0.064	0.000		-0.004	0.056	-0.002	
Diabetes status at age 50 (imputed)	0.153***	0.035	0.006		0.060	0.042	0.004		-0.009	0.041	-0.003	
Init. of Ever smoked	0.209***	0.024	0.007		0.069**	0.030	0.004		0.051**	0.022	0.019	
Smoking status at age 50 (imputed)	0.250***	0.024	0.010		0.087***	0.029	0.005		0.029	0.024	0.011	
Max(0, two-year lag age - 73)	0.006**	0.002	0.000									
Splined two-year lag of BMI <= log(30)	-0.266**	0.103	-0.009									
Splined two-year lag of BMI > log(30)	0.894***	0.131	0.030									
Splined init of BMI age 50 <= log(30)	0.053	0.104	0.002									
Splined init of BMI age 50 > log(30)	0.035	0.143	0.001									
Log of years between current interview and previous	0.183***	0.049	0.006		0.144**	0.059	0.009		0.548***	0.055	0.206	
Two-year lag of R working for pay					-0.551***	0.037	-0.040		-0.204***	0.031	-0.077	
Two-year lag of (IHT of earnings in 1000s)/100, zero otherwise					-0.603	0.891	-0.036		-3.093***	0.712	-1.165	
Two-year lag of Non-pension wlth(hatotb) not zero					0.121***	0.045	0.006		0.177***	0.048	0.065	
Two-year lag of (IHT of hh wlth in 1000s)/100, zero otherwise					-2.311***	0.391	-0.138		0.124	0.389	0.047	
Two-year lag of Claiming SSDI					2.699***	0.029	0.685		-1.212***	0.036	-0.343	
nraplus10					0.320***	0.053	0.022					
nraplus9					0.500***	0.063	0.045					
nraplus8					0.478***	0.062	0.042					
nraplus7					0.383***	0.063	0.032					
nraplus6					0.472***	0.061	0.042					
nraplus5					0.444***	0.061	0.038					
nraplus4					0.475***	0.060	0.042					
nraplus3					0.588***	0.058	0.057					
nraplus2					0.520***	0.058	0.048					
nraplus1					0.379***	0.059	0.031					
Two-year lag of Claiming DB									0.023	0.024	0.009	
Respondent is at the EEA age (62) or up to two years older									0.782***	0.033	0.294	
Respondent is at their NRA age or two years older									0.760***	0.029	0.295	
Years to NRA for those not year at NRA									-0.319***	0.014	-0.120	
Years past NRA for those older than NRA									-0.096***	0.003	-0.036	
cons	-2.737***	0.310			-2.566***	0.086			-0.205***	0.071		

	R live in nursing		R live in nursing		R working for pay		R working for pay	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	-0.313***	0.041	-0.002		0.047**	0.019	0.017	
Hispanic	-0.516***	0.060	-0.003		0.008	0.024	0.003	
Less than high school	-0.043	0.034	-0.000		-0.078***	0.022	-0.027	
Some college and above	0.008	0.033	0.000		0.065***	0.015	0.023	
Male	-0.067	0.042	-0.001		0.120***	0.019	0.043	
Male AND Less than high school	0.029	0.058	0.000		0.036	0.032	0.013	
Male AND Non-Hispanic Black	0.332***	0.064	0.005		-0.097***	0.029	-0.034	
Male AND Hispanic	0.241***	0.094	0.003		0.019	0.035	0.007	
Male AND Some college and above	0.002	0.055	0.000		0.012	0.023	0.004	
Min(63, two-year lag of age)	0.031***	0.008	0.000					
Min(Max(0, two-year lag age - 63), 73 - 63)	0.049***	0.005	0.000					
Two-year lag of Heart disease	-0.037	0.025	-0.000		-0.053***	0.015	-0.019	
Two-year lag of Stroke	0.186***	0.029	0.002		-0.148***	0.028	-0.051	
Two-year lag of Cancer	-0.037	0.030	-0.000		-0.045**	0.019	-0.016	
Two-year lag of Hypertension	-0.037	0.024	-0.000		-0.092***	0.011	-0.033	
Two-year lag of Diabetes	0.097***	0.028	0.001		-0.067***	0.016	-0.024	
Two-year lag of Lung disease	-0.067*	0.036	-0.001		-0.125***	0.022	-0.043	
Two-year lag of Has exactly 1 IADL	0.320***	0.033	0.004		-0.184***	0.025	-0.062	
Two-year lag of Has 2 or more IADLs	0.711***	0.032	0.017		-0.371***	0.041	-0.119	
Two-year lag of Has exactly 1 ADL	0.130***	0.033	0.001		-0.107***	0.023	-0.037	
Two-year lag of Has exactly 2 ADLs	0.212***	0.042	0.003		-0.298***	0.039	-0.097	
Two-year lag of Has 3 or more ADLs	0.328***	0.037	0.005		-0.231***	0.041	-0.077	
Two-year lag of Widowed	0.135***	0.026	0.001		0.021	0.018	0.008	
Heart problem status at age 50 (1/0)-imputed	0.131	0.097	0.001		-0.003	0.052	-0.001	
Stroke status at age 50 (1/0)-imputed	0.169	0.133	0.002		0.100	0.076	0.036	
Cancer status at age 50 (1/0)-imputed	0.110	0.077	0.001		0.021	0.032	0.007	
Diabetes status at age 50 (imputed)	0.120**	0.052	0.001		-0.041*	0.025	-0.014	
Init. of Ever smoked	0.081***	0.028	0.001		-0.016	0.013	-0.006	
Smoking status at age 50 (imputed)	-0.050*	0.030	-0.000		-0.100***	0.014	-0.035	
Max(0, two-year lag age - 73)	0.050***	0.002	0.000					
Log of years between current interview and previous	0.896***	0.065	0.008		-0.127***	0.029	-0.045	
Two-year lag of R working for pay					1.688***	0.014	0.564	
Two-year lag of (IHT of earnings in 1000s)/100, zero otherwise					14.523***	0.352	5.146	
Two-year lag of Non-pension wlth(hatotb) not zero	-0.151***	0.044	-0.002		0.223***	0.034	0.075	
Two-year lag of (IHT of hh wlth in 1000s)/100, zero otherwise	-4.681***	0.448	-0.044		-1.362***	0.219	-0.483	
Two-year lag of Claiming SSDI					-0.380***	0.032	-0.122	
Two-year lag of Claiming OASI - Reports receiving SS retirement income and 62+					0.075***	0.018	0.026	
Two-year lag of Claiming DB					-0.058***	0.013	-0.021	
Respondent is at the EEA age (62) or up to two years older					-0.155***	0.019	-0.053	
Respondent is at their NRA age or two years older					-0.081***	0.020	-0.028	
Years to NRA for those not year at NRA					0.051***	0.002	0.018	
Years past NRA for those older than NRA					-0.032***	0.002	-0.011	
Two-year lag of R live in nursingh ome at interview	2.352***	0.045	0.339					
Seasonally Adjusted Unemployment Rate					-0.005*	0.003	-0.002	
cons	-5.262***	0.464			-1.454***	0.047		

note: .01 - ***; .05 - **; .1 - *;

	Smoking status (smkstat) coefficients		Smoking status (smkstat) marginal effects					
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	-0.022*	0.013	0.007		-0.006		-0.000	
Hispanic	-0.169***	0.016	0.056		-0.053		-0.003	
Less than high school	0.002	0.013	-0.001		0.001		0.000	
Some college and above	0.091***	0.010	-0.028		0.027		0.002	
Male	0.525***	0.013	-0.160		0.149		0.011	
Male AND Less than high school	0.026	0.021	-0.008		0.008		0.000	
Male AND Non-Hispanic Black	-0.136***	0.020	0.045		-0.042		-0.002	
Male AND Hispanic	0.144***	0.025	-0.043		0.040		0.003	
Male AND Some college and above	-0.219***	0.016	0.072		-0.069		-0.003	
Min(63, two-year lag of age)	-0.000	0.001	0.000		-0.000		-0.000	
Min(Max(0, two-year lag age - 63), 73 - 63)	-0.008***	0.001	0.003		-0.002		-0.000	
Max(0, two-year lag age - 73)	-0.014***	0.001	0.004		-0.004		-0.000	
Two-year lag of Heart disease	0.072***	0.010	-0.022		0.021		0.001	
Two-year lag of Stroke	0.051***	0.015	-0.016		0.015		0.001	
Two-year lag of Cancer	0.064***	0.012	-0.020		0.019		0.001	
Two-year lag of Hypertension	0.001	0.008	-0.000		0.000		0.000	
Two-year lag of Diabetes	-0.014	0.011	0.004		-0.004		-0.000	
Two-year lag of Lung disease	0.193***	0.014	-0.057		0.053		0.004	
Two-year lag of R had heart attack since last wave	0.098***	0.028	-0.030		0.028		0.002	
Two-year lag of Has exactly 1 IADL	0.046***	0.015	-0.014		0.013		0.001	
Two-year lag of Has 2 or more IADLs	0.002	0.018	-0.001		0.001		0.000	
Two-year lag of Has exactly 1 ADL	0.038***	0.014	-0.012		0.011		0.001	
Two-year lag of Has exactly 2 ADLs	0.034*	0.021	-0.011		0.010		0.001	
Two-year lag of Has 3 or more ADLs	-0.012	0.020	0.004		-0.003		-0.000	
Two-year lag of Current smoking	2.605***	0.016	-0.375		-0.017		0.392	
Two-year lag of Widowed	-0.035***	0.011	0.011		-0.011		-0.001	
Heart problem status at age 50 (1/0)-imputed	0.080**	0.034	-0.024		0.023		0.002	
Stroke status at age 50 (1/0)-imputed	-0.279***	0.051	0.095		-0.092		-0.003	
Cancer status at age 50 (1/0)-imputed	0.018	0.022	-0.006		0.005		0.000	
Diabetes status at age 50 (imputed)	0.005	0.017	-0.002		0.002		0.000	
Smoking status at age 50 (imputed)	1.960***	0.013	-0.441		0.313		0.128	
Splined two-year lag of BMI <= log(30)	-0.085*	0.045	0.027		-0.025		-0.001	
Splined two-year lag of BMI > log(30)	0.323***	0.059	-0.102		0.096		0.006	
Splined init of BMI age 50 <= log(30)	-0.002	0.045	0.000		-0.000		-0.000	
Splined init of BMI age 50 > log(30)	-0.245***	0.063	0.077		-0.073		-0.004	
Log of years between current interview and previous	-0.004	0.020	0.001		-0.001		-0.000	
Init. of Ever smoked								
Two-year lag of demented								
Two-year lag of CIND								
Two-year lag of good memory								
Two-year lag of fair memory								

	ADL status (adlstat) coefficients		ADL status (adlstat) marginal effects							
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	0.110***	0.014	-0.025		0.014		0.006		0.005	
Hispanic	0.174***	0.018	-0.041		0.022		0.010		0.009	
Less than high school	0.121***	0.014	-0.028		0.015		0.007		0.006	
Some college and above	-0.038***	0.013	0.008		-0.005		-0.002		-0.002	
Male	-0.025	0.016	0.006		-0.003		-0.001		-0.001	
Male AND Less than high school	-0.015	0.023	0.003		-0.002		-0.001		-0.001	
Male AND Non-Hispanic Black	-0.001	0.023	0.000		-0.000		-0.000		-0.000	
Male AND Hispanic	-0.058**	0.028	0.013		-0.007		-0.003		-0.002	
Male AND Some college and above	-0.041**	0.020	0.009		-0.005		-0.002		-0.002	
Min(63, two-year lag of age)	0.007***	0.002	-0.001		0.001		0.000		0.000	
Min(Max(0, two-year lag age - 63), 73 - 63)	0.017***	0.002	-0.004		0.002		0.001		0.001	
Max(0, two-year lag age - 73)	0.038***	0.001	-0.008		0.005		0.002		0.002	
Two-year lag of Heart disease	0.109***	0.011	-0.025		0.014		0.006		0.005	
Two-year lag of Stroke	0.234***	0.014	-0.058		0.031		0.014		0.013	
Two-year lag of Cancer	0.053***	0.013	-0.012		0.007		0.003		0.002	
Two-year lag of Hypertension	0.055***	0.009	-0.012		0.007		0.003		0.002	
Two-year lag of Diabetes	0.080***	0.011	-0.018		0.010		0.004		0.004	
Two-year lag of Lung disease	0.212***	0.014	-0.051		0.028		0.013		0.011	
Two-year lag of R had heart attack since last wave	0.022	0.029	-0.005		0.003		0.001		0.001	
Two-year lag of Has exactly 1 IADL	0.409***	0.014	-0.108		0.055		0.027		0.026	
Two-year lag of Has 2 or more IADLs	0.707***	0.016	-0.207		0.095		0.053		0.059	
Two-year lag of Has exactly 1 ADL	0.975***	0.012	-0.304		0.125		0.078		0.100	
Two-year lag of Has exactly 2 ADLs	1.368***	0.017	-0.465		0.147		0.117		0.201	
Two-year lag of Has 3 or more ADLs	1.891***	0.018	-0.643		0.134		0.143		0.366	
Two-year lag of Current smoking	0.108***	0.014	-0.025		0.014		0.006		0.005	
Two-year lag of Widowed	0.030***	0.012	-0.007		0.004		0.002		0.001	
Heart problem status at age 50 (1/0)-imputed	0.042	0.035	-0.009		0.005		0.002		0.002	
Stroke status at age 50 (1/0)-imputed	0.115**	0.049	-0.027		0.015		0.007		0.006	
Cancer status at age 50 (1/0)-imputed	0.058**	0.026	-0.013		0.007		0.003		0.003	
Diabetes status at age 50 (imputed)	0.125***	0.018	-0.029		0.016		0.007		0.006	
Smoking status at age 50 (imputed)	0.060***	0.012	-0.013		0.007		0.003		0.003	
Splined two-year lag of BMI <= log(30)	-0.383***	0.050	0.085		-0.048		-0.021		-0.017	
Splined two-year lag of BMI > log(30)	0.672***	0.061	-0.149		0.083		0.036		0.029	
Splined init of BMI age 50 <= log(30)	0.611***	0.051	-0.135		0.076		0.033		0.027	
Splined init of BMI age 50 > log(30)	0.294***	0.064	-0.065		0.036		0.016		0.013	
Log of years between current interview and previous	0.231***	0.024	-0.051		0.029		0.012		0.010	
Init. of Ever smoked	0.008	0.011	-0.002		0.001		0.000		0.000	
Two-year lag of demented										
Two-year lag of CIND										
Two-year lag of good memory										
Two-year lag of fair memory										

	IADL status (iadlstat) coefficients		IADL status (iadlstat) marginal effects					
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	0.101***	0.015	-0.020		0.012		0.008	
Hispanic	0.125***	0.019	-0.025		0.015		0.010	
Less than high school	0.164***	0.015	-0.033		0.020		0.013	
Some college and above	-0.043***	0.014	0.008		-0.005		-0.003	
Male	-0.010	0.017	0.002		-0.001		-0.001	
Male AND Less than high school	0.023	0.024	-0.004		0.003		0.002	
Male AND Non-Hispanic Black	0.018	0.025	-0.003		0.002		0.001	
Male AND Hispanic	-0.037	0.030	0.007		-0.004		-0.003	
Male AND Some college and above	-0.084***	0.022	0.015		-0.009		-0.006	
Min(63, two-year lag of age)	-0.005***	0.002	0.001		-0.001		-0.000	
Min(Max(0, two-year lag age - 63), 73 - 63)	0.022***	0.002	-0.004		0.003		0.002	
Max(0, two-year lag age - 73)	0.049***	0.001	-0.009		0.006		0.003	
Two-year lag of Heart disease	0.100***	0.011	-0.019		0.012		0.008	
Two-year lag of Stroke	0.271***	0.015	-0.058		0.034		0.024	
Two-year lag of Cancer	0.038***	0.014	-0.007		0.004		0.003	
Two-year lag of Hypertension	0.075***	0.010	-0.014		0.009		0.005	
Two-year lag of Diabetes	0.106***	0.012	-0.021		0.013		0.008	
Two-year lag of Lung disease	0.221***	0.015	-0.046		0.027		0.019	
Two-year lag of R had heart attack since last wave	0.047	0.031	-0.009		0.006		0.004	
Two-year lag of Has exactly 1 IADL	0.971***	0.013	-0.274		0.131		0.143	
Two-year lag of Has 2 or more IADLs	1.724***	0.017	-0.559		0.179		0.380	
Two-year lag of Has exactly 1 ADL	0.435***	0.014	-0.100		0.057		0.043	
Two-year lag of Has exactly 2 ADLs	0.573***	0.019	-0.143		0.077		0.066	
Two-year lag of Has 3 or more ADLs	0.760***	0.019	-0.203		0.104		0.099	
Two-year lag of Current smoking	0.162***	0.015	-0.032		0.020		0.013	
Two-year lag of Widowed	0.008	0.012	-0.002		0.001		0.001	
Heart problem status at age 50 (1/0)-imputed	0.047	0.038	-0.009		0.005		0.003	
Stroke status at age 50 (1/0)-imputed	0.094*	0.052	-0.019		0.011		0.007	
Cancer status at age 50 (1/0)-imputed	0.029	0.028	-0.006		0.003		0.002	
Diabetes status at age 50 (imputed)	0.098***	0.020	-0.019		0.012		0.008	
Smoking status at age 50 (imputed)	0.005	0.013	-0.001		0.001		0.000	
Splined two-year lag of BMI <= log(30)	-0.810***	0.052	0.151		-0.094		-0.058	
Splined two-year lag of BMI > log(30)	0.263***	0.067	-0.049		0.030		0.019	
Splined init of BMI age 50 <= log(30)	0.546***	0.054	-0.102		0.063		0.039	
Splined init of BMI age 50 > log(30)	0.306***	0.071	-0.057		0.035		0.022	
Log of years between current interview and previous	0.240***	0.025	-0.045		0.028		0.017	
Init. of Ever smoked	0.019*	0.012	-0.004		0.002		0.001	
Two-year lag of demented								
Two-year lag of CIND								
Two-year lag of good memory								
Two-year lag of fair memory								

	Cognitive state (cogstate) coefficients		Cognitive state (cogstate) marginal effects					
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
Non-Hispanic Black	-0.430***	0.014	0.017		0.103		-0.120	
Hispanic	-0.314***	0.017	0.012		0.074		-0.086	
Less than high school	-0.343***	0.014	0.012		0.080		-0.092	
Some college and above	0.252***	0.013	-0.007		-0.054		0.061	
Male	-0.121***	0.015	0.003		0.026		-0.030	
Male AND Less than high school	0.012	0.021	-0.000		-0.002		0.003	
Male AND Non-Hispanic Black	0.036*	0.022	-0.001		-0.008		0.009	
Male AND Hispanic	0.123***	0.027	-0.003		-0.025		0.028	
Male AND Some college and above	0.046**	0.020	-0.001		-0.010		0.011	
Min(63, two-year lag of age)	-0.007***	0.002	0.000		0.001		-0.002	
Min(Max(0, two-year lag age - 63), 73 - 63)	-0.032***	0.001	0.001		0.007		-0.008	
Max(0, two-year lag age - 73)	-0.043***	0.001	0.001		0.009		-0.010	
Two-year lag of Heart disease	0.008	0.011	-0.000		-0.002		0.002	
Two-year lag of Stroke	-0.182***	0.015	0.006		0.042		-0.048	
Two-year lag of Cancer	0.029**	0.013	-0.001		-0.006		0.007	
Two-year lag of Hypertension	-0.029***	0.009	0.001		0.006		-0.007	
Two-year lag of Diabetes	-0.079***	0.012	0.002		0.017		-0.020	
Two-year lag of Lung disease	-0.029*	0.015	0.001		0.006		-0.007	
Two-year lag of R had heart attack since last wave	-0.011	0.030	0.000		0.002		-0.003	
Two-year lag of Has exactly 1 IADL	-0.226***	0.015	0.008		0.052		-0.060	
Two-year lag of Has 2 or more IADLs	-0.325***	0.019	0.013		0.078		-0.090	
Two-year lag of Has exactly 1 ADL	-0.063***	0.015	0.002		0.014		-0.016	
Two-year lag of Has exactly 2 ADLs	-0.054**	0.021	0.002		0.012		-0.013	
Two-year lag of Has 3 or more ADLs	-0.075***	0.021	0.002		0.017		-0.019	
Two-year lag of Current smoking	-0.077***	0.014	0.002		0.017		-0.019	
Two-year lag of Widowed	-0.046***	0.011	0.001		0.010		-0.011	
Heart problem status at age 50 (1/0)-imputed	-0.036	0.037	0.001		0.008		-0.009	
Stroke status at age 50 (1/0)-imputed	-0.157***	0.051	0.005		0.036		-0.041	
Cancer status at age 50 (1/0)-imputed	0.009	0.028	-0.000		-0.002		0.002	
Diabetes status at age 50 (imputed)	-0.034*	0.019	0.001		0.007		-0.008	
Smoking status at age 50 (imputed)	-0.041***	0.012	0.001		0.009		-0.010	
Splined two-year lag of BMI <= log(30)	0.762***	0.050	-0.021		-0.165		0.186	
Splined two-year lag of BMI > log(30)	0.248***	0.067	-0.007		-0.054		0.061	
Splined init of BMI age 50 <= log(30)	-0.423***	0.051	0.012		0.091		-0.103	
Splined init of BMI age 50 > log(30)	-0.249***	0.069	0.007		0.054		-0.061	
Log of years between current interview and previous	-0.244***	0.024	0.007		0.053		-0.060	
Init. of Ever smoked	0.009	0.011	-0.000		-0.002		0.002	
Two-year lag of demented	-1.828***	0.020	0.285		0.350		-0.635	
Two-year lag of CIND	-1.007***	0.010	0.066		0.253		-0.319	
Two-year lag of good memory	0.319***	0.018	-0.011		-0.073		0.083	
Two-year lag of fair memory	0.175***	0.018	-0.004		-0.036		0.041	

note: .01 - ***; .05 - **; .1 - *;

	Log(BMI) (logbmi) coefficients		Log(BMI) (logbmi) marginal effects	
	coef	p-value	coef	p-value
Male	0.000	0.001	0.000	
Non-Hispanic Black	-0.002**	0.001	-0.002	
Hispanic	-0.002**	0.001	-0.002	
Less than high school	-0.002***	0.001	-0.002	
Some college and above	-0.000	0.001	-0.000	
Male AND Less than high school	0.000	0.001	0.000	
Male AND Non-Hispanic Black	-0.005***	0.001	-0.005	
Male AND Hispanic	-0.001	0.001	-0.001	
Male AND Some college and above	-0.001	0.001	-0.001	
Min(63, two-year lag of age)	-0.000**	0.000	-0.000	
Min(Max(0, two-year lag age - 63), 73 - 63)	-0.001***	0.000	-0.001	
Max(0, two-year lag age - 73)	-0.002***	0.000	-0.002	
Two-year lag of Heart disease	-0.000	0.001	-0.000	
Two-year lag of Stroke	-0.002***	0.001	-0.002	
Two-year lag of Cancer	-0.001	0.001	-0.001	
Two-year lag of Hypertension	0.004***	0.000	0.004	
Two-year lag of Diabetes	-0.001	0.001	-0.001	
Two-year lag of Lung disease	-0.005***	0.001	-0.005	
Two-year lag of R had heart attack since last wave	0.004***	0.002	0.004	
Two-year lag of Has exactly 1 IADL	-0.002*	0.001	-0.002	
Two-year lag of Has 2 or more IADLs	-0.005***	0.001	-0.005	
Two-year lag of Has exactly 1 ADL	0.001*	0.001	0.001	
Two-year lag of Has exactly 2 ADLs	0.001	0.001	0.001	
Two-year lag of Has 3 or more ADLs	0.001	0.001	0.001	
Two-year lag of Current smoking	-0.012***	0.001	-0.012	
Two-year lag of Widowed	0.001	0.001	0.001	
Heart problem status at age 50 (1/0)-imputed	0.001	0.002	0.001	
Stroke status at age 50 (1/0)-imputed	-0.005	0.003	-0.005	
Cancer status at age 50 (1/0)-imputed	0.001	0.001	0.001	
Diabetes status at age 50 (imputed)	-0.004***	0.001	-0.004	
Init. of Ever smoked	0.001**	0.001	0.001	
Smoking status at age 50 (imputed)	0.002***	0.001	0.002	
Splined two-year lag of BMI <= log(30)	0.812***	0.003	0.812	
Splined two-year lag of BMI > log(30)	0.834***	0.004	0.834	
Splined init of BMI age 50 <= log(30)	0.139***	0.003	0.139	
Splined init of BMI age 50 > log(30)	0.099***	0.004	0.099	
Log of years between current interview and previous	-0.011***	0.001	-0.011	
Init. of	0.000	0.000	0.000	
_cons	0.119	0.076		

note: .01 - ***; .05 - **; .1 - *;

	a		b		c	
	AIME	**Quarters worked**	**AIME**	**Quarters worked**	**AIME**	**Quarters worked**
male	1.177042	0.721902	0.685888	0.493853	3.133855	0.640603
black	0.182828	0.262259	-0.03747	-0.03145	-0.21378	-0.23367
hispanic	-0.10815	-0.01097	-0.39495	-0.3881	-0.62464	-0.67265
less than high school	-0.29051	-0.20053	-0.38688	-0.38692	-0.7385	-0.83145
college	0.391471	0.033239	0.31378	0.030084	0.185081	-0.06804
cancer ever	0.015336	-0.05549	0.053945	0.018034	0.107717	0.089697
diabetes ever	-0.04335	-0.02971	-0.01551	0.030966	-0.16512	-0.1252
high blood pressure ever	0.038134	0.047507	0.020347	0.039341	0.102759	0.07145
heart disease ever	-0.00773	-0.00721	-0.07891	-0.02907	-0.20946	-0.24406
lung disease ever	-0.07839	-0.0693	-0.12824	-0.1311	-0.18279	-0.16386
stroke ever	-0.08565	-0.08317	-0.05645	-0.03232	-0.11142	0.105998
any limits activities daily living					0.099986	0.047761
any limits instrumental activities daily living					-0.01069	-0.04193
working			-0.01155	0.332013	0.240934	0.522726
age					0.051655	0.127688
age55	0.396541	0.219046	0.094877	0.281444		
age60	0.889618	0.687244	0.099726	0.525265		
age65	0.898157	0.747699	-0.16031	0.367211		
age70	0.771615	0.675703	-1.29151	-1.07111		
age75	0.709974	0.719848	-1.24782	-0.99143		
age80	0.463509	0.537322	-1.65716	-1.31495		
age85	0.366938	0.299211	-1.57629	-1.28759		
cohort	0.049492	0.217586				
OASI income	0.165017	0.160295				
OASI income^2	-0.00343	-0.00293				
cohort*OASI income	-0.00115	-0.00828				
cohort*OASI income^2	0.000334	0.000196				
Log earnings			21.66689	16.3403	27.774	21.09548
log wealth			4.117933	0.547482	4.706552	1.448593
years worked	0.032552	0.053106	0.022624	0.026314		
male*black	-0.58025	-0.38046	-0.41849	-0.31465	-0.30406	-0.09088
male*hispanic	-0.34483	-0.2234	-0.03986	-0.01205	0.28858	0.334378
male*less than hs	0.093876	0.204713	0.253101	0.255572	0.600842	0.602072
male*college	-0.26252	-0.21113	-0.09874	-0.1406	0.121581	0.116927
male*working			0.045535	-0.02175	0.002846	-0.06738
male*cancer					-0.24448	-0.14202
male*diabetes					0.046893	0.080827
male*high blood pressure					0.089648	0.06727
male*heart disease					0.05002	0.25743
male* lung disease					-0.19528	-0.08871
male*stroke					0.063189	-0.04593
male*any limits activities daily living					0.081665	0.223549
male*any limits instrumental activities daily living					-0.07976	-0.13784
male*Log earnings					-2.27249	-2.53832
male*log wealth					2.249712	1.936031
male*age					-0.04993	-0.00762
__cons	-0.87213	-1.27375	1.445851	1.371986	-1.2748	-5.24469
cut_1	0	0	0	0	0	0
cut_2	0.612591	0.707338	0.575759	0.587855	0.469469	0.292282
cut_3	0.996756	1.09117	0.92506	0.969767	0.801709	0.644248
cut_4	1.272445	1.41647	1.213057	1.273226	1.023445	0.900791
cut_5	1.504415	1.7124	1.429905	1.487386	1.193377	1.081617
cut_6	1.720373	1.920925	1.632075	1.666681	1.385231	1.202616
cut_7	1.920916	2.139052	1.82155	1.870275	1.520652	1.346931
cut_8	2.11321	2.323625	1.981069	2.025261	1.648648	1.508258
cut_9	2.284868	2.478047	2.156447	2.162239	1.804837	1.617527
cut_10	2.448629	2.633768	2.286931	2.307898	1.942447	1.73703
cut_11	2.591388	2.791618	2.432724	2.455739	2.070862	1.831576
cut_12	2.740394	2.928689	2.57148	2.591979	2.214899	1.934354
cut_13	2.87989	3.068272	2.696071	2.726213	2.346294	2.035432
cut_14	3.013967	3.188075	2.802216	2.857009	2.446485	2.134892
cut_15	3.138041	3.319818	2.910282	2.978495	2.547237	2.230442
cut_16	3.262587	3.420097	3.019897	3.06362	2.660737	2.341662
cut_17	3.393148	3.51907	3.13062	3.174029	2.761803	2.445696
cut_18	3.500922	3.620102	3.234248	3.296814	2.850269	2.547572
cut_19	3.615035	3.694185	3.333921	3.38588	2.936522	2.633842
cut_20	3.728316	3.772639	3.436813	3.490147	3.021477	2.670219
cut_21	3.84679	3.84692	3.537233	3.589097	3.123238	2.782172
cut_22	3.948418	3.93768	3.62763	3.689806	3.195826	2.858657
cut_23	4.060413	4.024152	3.719278	3.780984	3.272101	2.93386
cut_24	4.162077	4.085137	3.817715	3.839771	3.357198	3.025142
cut_25	4.291537	4.176407	3.901104	3.937439	3.448403	3.112226
cut_26	4.389674	4.262044	3.987418	4.038476	3.543015	3.220112
cut_27	4.487396	4.352692	4.068249	4.17329	3.658828	3.264717
cut_28	4.599493	4.421259	4.14335	4.23918	3.772789	3.348983
cut_29	4.729225	4.508801	4.219557	4.364964	3.876807	3.425467
cut_30	4.87085	4.570422	4.298667	4.445345	3.986011	3.528381
cut_31	5.007144	4.661642	4.381464	4.575721	4.052048	3.584994
cut_32	5.153517	4.752852	4.467215	4.697979	4.157175	3.659102
cut_33	5.305508	4.85072	4.551568	4.829668	4.282192	3.740076
cut_34	5.474605	4.954851	4.636887	4.974397	4.392733	3.797671
cut_35	5.672066	5.05971	4.729155	5.088255	4.538928	3.901142
cut_36	5.864491	5.185555	4.843684	5.269043	4.653784	4.000171
cut_37	6.119877	5.34456	4.961928	5.500027	4.822141	4.16956
cut_38	6.464427	5.522038	5.133382	5.861384	4.954259	4.301558
cut_39	6.902466	5.85987	5.417442	6.528249	5.353137	4.680165
vc	1		1		1	
vc	0.681825	1	0.780831	1	0.788228	1

	Reporting OASI income
male	0.30273
black	0.098371
hispanic	-0.24655
less than high schoo	-0.32356
college	0.016726
years worked	0.040067
male*black	0
male*hispanic	0.197965
male*less than hs	0.711774
male*college	0.145946
age55	-0.0459
age60	-0.35996
age65	-0.19865
age70	-0.51445
age75	-0.47976
age80	-0.76139
age85	-1.31447
cons	1.884816