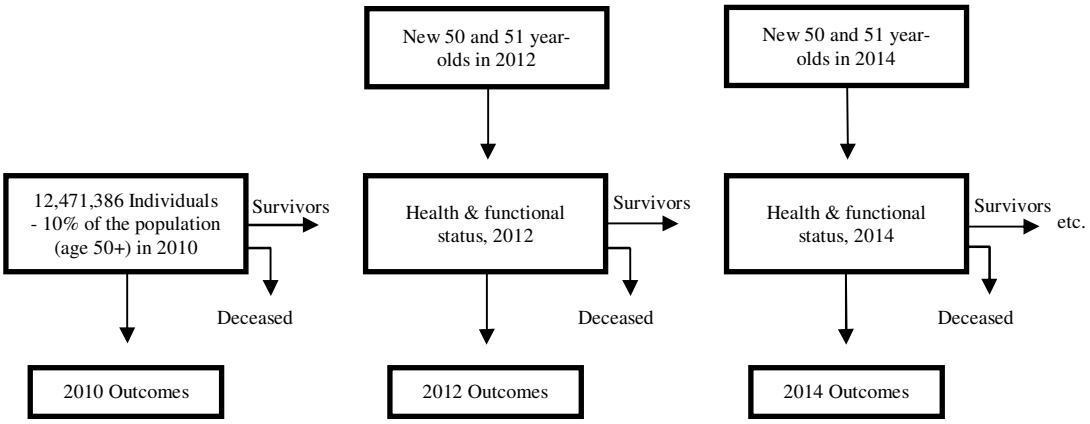
Online Appendix 1: Technical Appendix

Appendix Figure 1 presents an overview of the structure of the microsimulation. The simulation starts in 2010 with nearly 12.5 Million hypothetical individuals age 50+ (10% of the population in 2010; (Statistics Bureau 2010)). The simulation model estimates the risk of developing 19 diseases for each individual. The model updates the health status and mortality risk for each individual. At the end of each cycle, some of the individuals die, and the rest age 2 years and are transitioned to the next cycle. In addition, a new cohort of 50 and 51 year-old individuals are added to the population in 2012 to replenish the youngest cohorts. The same process is repeated for the subsequent cycles (2014, 2016, …, etc.).

Appendix Figure 1: Overview of the microsimulation model



The microsimulation consists of two main modules: a core module that describes the health and mortality of the population, and a set of secondary modules that forecast disability and may be adapted to other outcomes such as healthcare utilization, medical spending, and long-term care in Japan. The secondary modules are based on the core module. This technical appendix focuses on the functionality of the core health transition module. (Jalal, Eggleston et al. 2015)

The core module describes the health status of each individual. Health status is defined by 19 conditions based on self-reported health conditions in JSTAR. The survey asks respondents about a multiplicity of health conditions. Self-reported measures of health conditions are based on a positive response for current or past treatment for a

medical condition, or from communication by a physician that the respondent has that specific health condition. We focus our analysis on diseases identified by our medical panel as the most relevant and costly in a Japanese population. The 19 conditions selected are presented in Appendix Table 1, along with their prevalence calculated by using the 2007 data.

Appendix Table 1: Summary Statistics

Variable	Obs	Mean
heart disease	3,708	0.13
hypertension	3,708	0.44
hyperlipidemia	3,708	0.16
CVD	3,708	0.05
diabetes	3,708	0.15
COPD	3,708	0.02
asthma	3,708	0.04
liver	3,708	0.05
ulcer	3,708	0.09
joint	3,708	0.08
broken hip	3,708	0.01
osteoporosis	3,708	0.06
eye disease	3,708	0.14
bladder	3,708	0.05
mental health	3,708	0.03
dementia	3,708	0.00
skin	3,708	0.04
cancer	3,708	0.04
other	3,708	0.16

The model's main variables are AGE_{it}, $GENDER_i$, $SMOKE_{it}$, BMI_{it}, and a set of 19 indicator variables $DISEASE_{it} = \{DISEASE1_{it},...,DISEASE19_{it}\}$ that reference the 19 chronic conditions, where i indexes the individual and t refers to time. In addition, we create an indicator variable $MORT_{it} = 1$ if the simulated individual dies during the simulation. The baseline cohort is defined at the initial time period ($t = 1$). This time period represents the first two years of the simulations (i.e., 2010 and 2011). The variables AGE, GENDER, SMOKE, BMI and DISEASE are sampled from JSTAR with replacement. These samples are repeated until the number of individuals in each age

and sex category are equal to the Japanese population distribution in 2010 (Statistics Bureau 2010).

After establishing the baseline cohort, the microsimulation iterates to the next time period ($t = 2$) by projecting the values of each variable for the next two years (i.e., 2012 and 2013). Thus, the variable $AGE_{it=2} = AGE_{it=1} + 2$. Since the 50 and 51 years individuals age to 52 and 53 years-old, respectively, at $t = 2$, new 50 and 51 year-old individuals are added to the simulation to replenish the youngest age group. The characteristics of these new individuals are sampled with replacement from the 50-55 year-old individuals in JSTAR, weighted by the age- and gender-specific projected population of 50 year-olds based on the official Japanese projections (National Institute of Popoulation and Social Security Research 2012).

Health transitions

JSTAR provides self-reported health status measures for each individual in 2007 and 2009. We use logit regressions to estimate the probability of transitioning to one of the 19 mutually exclusive health states in 2009 based on not having that health condition in 2007 and controlling for demographic and comorbid conditions in 2007. We project transitions of self-reported heart disease, hypertension, hyperlipidemia, diabetes, cancer, and fourteen other categories of disease. The independent variables include health status and basic demographic characteristics such as age, gender, smoking status or weight category, as measured at baseline in 2007. The coefficient estimates of these transitions models predict health status two years into the future (2009). We model these relationships as $H_t + 2 = g(H_t, X_t)$, using multivariate logit regression. Because these health states are measured by responses to questions such as "Have you ever been told by a doctor ...." we treat all health status states as absorbing states.

We choose the following sample selection criteria. Individuals must be at least 45 years old. This yields 3,862 respondents with a total of 7,724 interview years. We then drop observations of individuals with a missing value for any of our health measures of interest. Following this selection criterion, we arrive at the final estimation sample consisting of 2,526 individuals for 2007, 2,659 for 2009, and 1,854 individuals and 3,708 interview years for the pooled data. Most missing data occur for self-reported health

states. The health status measures include heart disease, hypertension, hyperlipidemia, cerebrovascular disease, diabetes, chronic obstructive pulmonary disease, asthma, liver disease, ulcer, joint disease, bone fractures/broken hip, osteoporosis, eye disease, bladder disease, mental health disorder, dementia, skin disease, cancer and all other diseases. Appendix Table 1 provides summary statistics of the baseline 2007 values of the independent variables used in the estimation, including the prevalence of the various disease states.

As noted previously, we treat all health conditions in JSTAR as absorbing states. For the 19 health states, the JSTAR questions are worded as "Have you been newly diagnosed with, or have you ever been diagnosed with ..." The question wordings define these conditions as absorbing states. In addition, we separately estimated the likelihood of transitioning out of the disease states but found little evidence of recovery for the listed medical conditions in our sample. As a result, we only model transitions into these states (without allowing for cure) in the following form: $ln\left(\frac{p_{i,j,t+2}}{1-p_{i,j,t+2}}\right) = \beta_0 + \boldsymbol{\gamma} \cdot \boldsymbol{X_{ijt}} + \varepsilon_{ijt}$, where $p_{i,j,t+2}$ is the probability of having the *j*-th condition for individual *i* at time *t+2* (2009); and $\mathbf{X_{ijt}}$ are demographic characteristics (age, and where appropriate, an indicator for BMI $\geq$ 23.5, and an indicator for heavy smoking, defined as > 20 cigarettes per day) and co-morbidities for individual *i* in time *t* (2007) that affect the onset of condition *j*.

The probabilities of the onset of the various conditions are assumed to be linear in the covariates. Age and male gender enter into all transition models, but the other covariates enter into the regression only if two medical doctors agree that they are likely causative factors in the onset of the specific disease model in question. Given the low prevalence of obesity in Japan, we choose a BMI value of 23.5 and greater to be a proxy for overweight. For smoking, because of the high number of smokers among Japanese males, we set the indicator variable for smoker if the respondent answers smoking 20 or more cigarettes per day in 2007.

The unit of observation is an interview-pair (for years 2007-2009). All independent variables are measured with a two-year lag, and represent the respondent's characteristics as of 2007. Transition probabilities are estimated only

using individuals who did not suffer from a specific condition at baseline (2007). As a result, the sample sizes for various health status transition regressions do vary. For example, consider a respondent who was interviewed in 2007 without cancer but with a heart condition. In 2009, he is diagnosed with cancer. This person's baseline condition included "heart disease," so he does not contribute to the heart disease transition model in any way. On the other hand, he contributes one observation to the cancer transition model. Because JSTAR currently only has two time points, we ignore clustering at the individual level because any given person will contribute at most once to a specific disease model.

Since JSTAR lacks data on individuals 80 years and older, we used the health transition module to age the JSTAR population, and sampled for those older than 80 years. We recognize this as an important limitation of the data since the number and type of chronic conditions may be different, especially in the later years of life. (The details of the mortality calculations are described below.)

Because JSTAR is not nationally representative, we generate sample weights by sex and age in five-year increments (50-54, 55-59, …, 75-79) by dividing the number of the Japanese population in each age group-sex category by the number of the JSTAR population in the same category, and normalizing the weights such that they sum to 1 across the JSTAR age group-sex categories. We use these weights as probability weights in our logit regressions to better match the JSTAR sample on age and sex with the national census data from 2007 (See Appendix Table 2).

Appendix Table 2: Sample Weights

		N (JSTAR)	% of total (JSTAR)	N (Japan census)	% (Japan census)	Sample weights
Males	50-54	230	0.061497326	4017000	0.084960132	0.095061572
	55-59	435	0.11631016	5161000	0.109155898	0.064576663
	60-64	370	0.098930481	4131000	0.087371248	0.060769333
	65-69	365	0.097593583	3747000	0.079249593	0.055875552
	70-74	383	0.102406417	3191000	0.067490112	0.045348093
	75-79	76	0.020320856	2407000	0.050908399	0.172382626
Females	50-54	256	0.068449198	4032000	0.085277384	0.085725801
	55-59	357	0.095454545	5271000	0.111482414	0.080362936
	60-64	361	0.096524064	4344000	0.091876229	0.065495824
	65-69	394	0.105347594	4091000	0.086525243	0.056515068
	70-74	411	0.109893048	3732000	0.078932341	0.049423194
	75-79	102	0.027272727	3157000	0.066771007	0.168463339
		3740		47281000		1

Mortality

At the end of each cycle, the probability of death for each individual is calculated as the sum of disease-specific mortality rates for that age and sex category[1], such that $m_i = \sum_{j=1} r_{asj}$, where m_i is the total mortality rate for individual i and r_{asj} is the mortality rate conditional on age, gender and disease.

We used the iterative proportional fitting (IPF) algorithm to calculate the conditional mortality rates from JSTAR data and the Japanese vital statistics data. The vital statistics provides aggregated information on the cause of death by age and gender, but no information is provided on other comorbidities at the time of death. To calculate the conditional mortality rates, we assume conditional independence of the disease-specific mortalities, such that the probability of any particular disease being the cause of death is independent on the other comorbidities that an individual has. For example, if 5% of patients who have only HD die from HD, under conditional independence, 5% of patient with HD+CA are also expected to die from HD. In the latter group, an additional 4% may die from cancer, for example. More formally, we assume that p(HD cause of death|HD) = p(HD casue of death|HD,CA,…). Later we test the effects of this assumption on the mortality rate calculations.

Appendix Table 3 illustrates the setup for the IPF algorithm for a particular age and sex combination. This table illustrates the distribution of individuals with unique disease profiles who are alive or dead due to one of the 19 diseases. For example, $m_{CA}|q_3$ represents the number of individuals who have heart disease and cancer and are expected to die from cancer. The cells that refer to diseases not in the disease profiles are set to zero because we assume that all diseases are observed. The column totals represent the total number of people with each particular disease profile. This data is known from JSTAR and scaled up to match the number of individuals in the population using the census data. Furthermore, the row totals represent the number of individuals who died in 2010 from each condition, and the total number of individuals alive. Since both the column and row margins are known, the IPF algorithm computes the number of people who are expected to die due to each condition for all disease profiles. The IPF converges when the sum of the cells in each row equals the row total and the sum of the cells on the columns are equal the column margin. The disease specific mortality rates (r_{asj}) are then calculated by dividing each column by the column totals.

Appendix Table 3: Setup for the Iterative Proportional Fitting Algorithm

Diseases Profile	Dead due to leading cause					Alive	Total
	HD	HTN	…	CA	Other		
HD	$m_{HD}\|q_1$	0	…	0	$m_{other}\|q_1$	$alive\|q_1$	q_1
HD+HTN	$m_{HD}\|q_2$	$m_{HTN}\|q_2$	…	0	$m_{other}\|q_2$	$alive\|q_2$	q_2
HD+CA	$m_{HD}\|q_3$	0	…	$m_{CA}\|q_3$	$m_{other}\|q_3$	$alive\|q_3$	q_3
…	…	…	…	…	…	…	…
Total	$\sum_i m_{HD}\|q_i$	$\sum_i m_{HTN}\|q_i$	…	$\sum_i m_{CA}\|q_i$	$\sum_i m_{other}\|q_i$	$\sum_i alive\|q_i$	$\sum_i q_i$

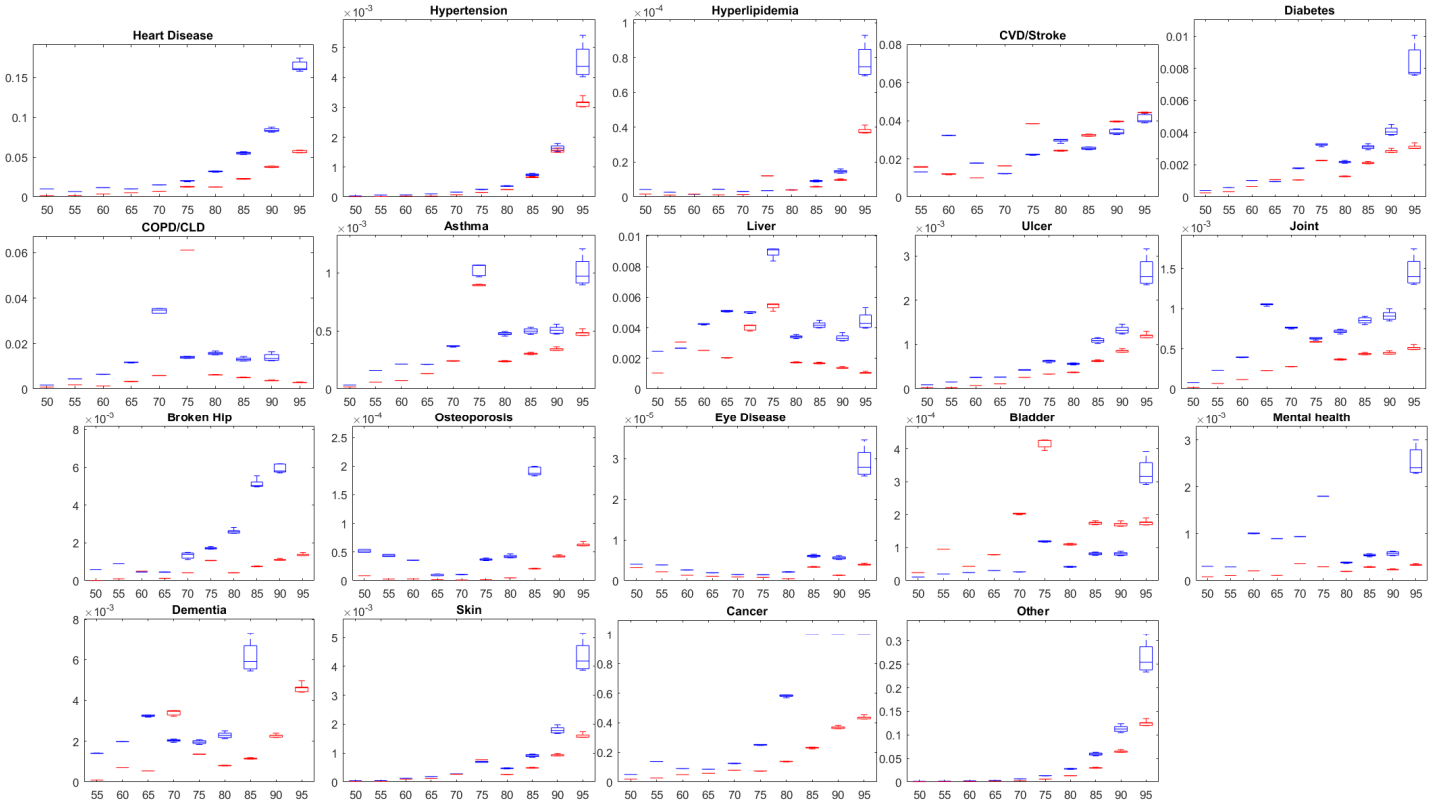
Note: The number in the cells represents the number of people who are expected to live or die from a particular constellation of conditions. The rows represent the combinations of the 19 disease categories in JSTAR; the columns represent the total number projected to die of a particular leading cause of death at a given point in time, as well as the total alive; and the final row shows the total number of deaths due to each of the 19 conditions. HD = heart disease, CA = cancer, HTN = hypertension.

Results

Conditional mortality

Appendix Figure 2 consists of a series of box-plots that illustrate the distribution of age-, sex-, and disease-specific 5-year mortality rates (r_{asj}) predicted with the IPF algorithm for all unique disease profiles. Overall, mortality rates increase with age and are generally higher for males than females except for bladder disease and urinary tract infections. Mortality rates are highest for cancer, followed by "other," a residual category that captures causes of death that are not included in the 18 specific categories and essentially represents the remaining age- and sex-specific mortality rate. Heart disease has the third highest mortality rate. Importantly, the mortality rate distributions over the various disease profiles and comorbidities are narrow, indicating that the conditional mortality independence is a suitable assumption because the mortality rates for the 19 conditions regardless of the associated comorbidities do not seem to vary significantly. In addition, we used the mean r_{asj} over all unique disease profiles to compute the number of people who are expected to die in Japan in 2010.

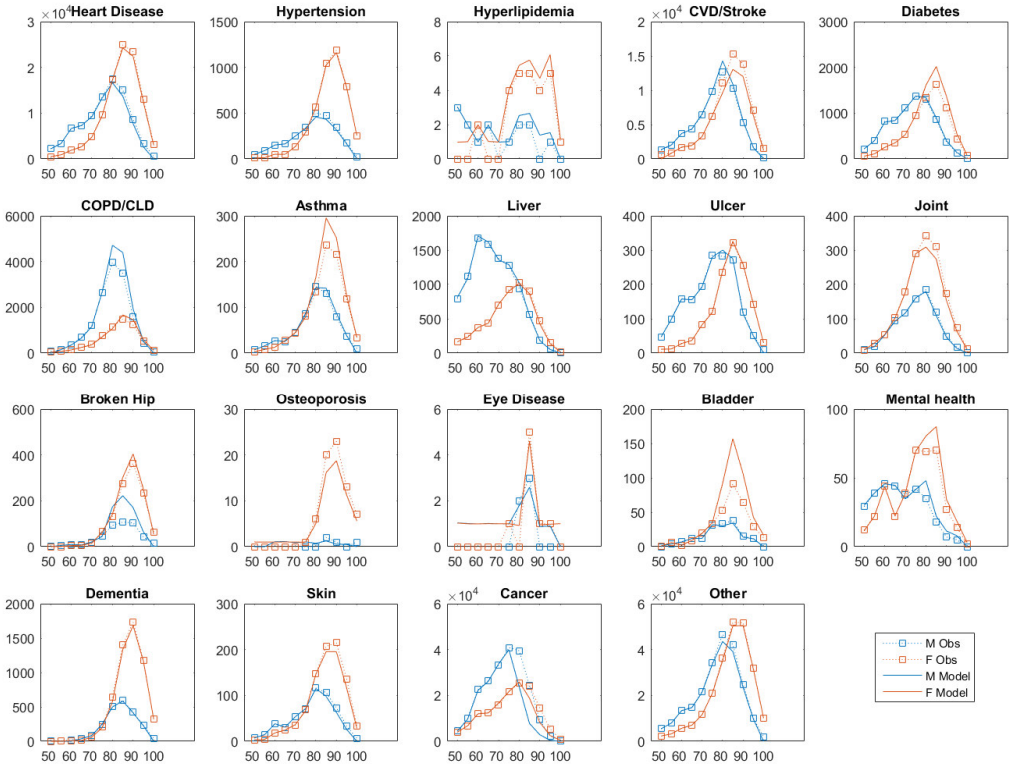
Appendix Figure 2: Age-, gender- and disease-specific mortality rate distributions for all 19 diseases



Note: Blue = male, Red = female. The boxes are the 95% confidence intervals; the central lines are the medians; and the whiskers are the most extreme points.

Appendix Figure 3 compares the IPF predicted deaths (solid line) to the observed data (dashed line with squares). The IPF results are nearly identical to the official observations, indicating that the IPF is capable of accurately reproducing disease-specific mortality.

Appendix Figure 3: Predicted vs. observed number of deaths by age and gender for 2010



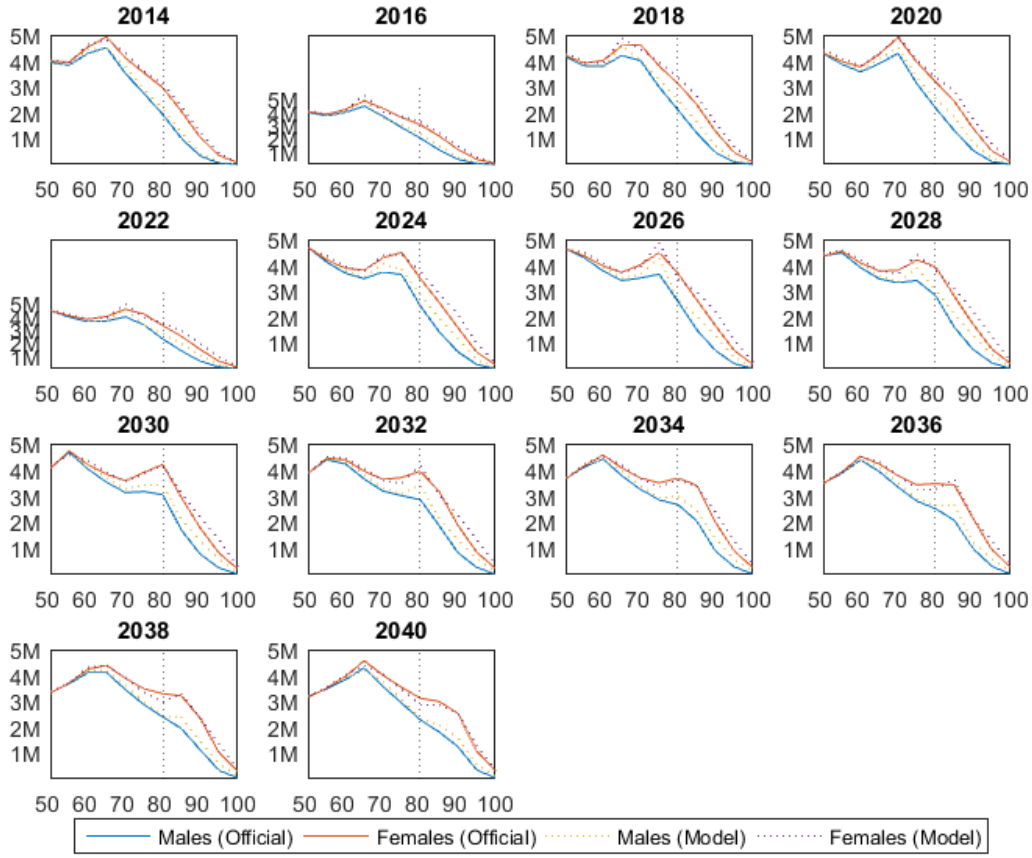
Note: M Obs = observed data for males, F Obs = observed data for females, M Model = IPF prediction for males, F Model = IPF predictions for females.

Population projections

Appendix Figure 4 compares the microsimulation predicted population size (solid line) to the 2010 census and the official Japanese projections for 2020, 2030 and 2040 (dashed line). The baseline results are identical because we are matching the baseline cohort to the 2010 census data. The microsimulation projections in future years are slightly higher than the official projections. The population size is expected to decrease,

as shown by the population pyramids (Figure 1), while the relative proportion of the elderly is expected to increase.

Appendix Figure 4: Population size from the microsimulation (solid lines) compared to official projections (dashed lines) for 2014-2040



Note: The official projections are from National Institute of Population and Social Security Research of Japan, median variant. M Obs = observed data for males, F Obs = observed data for females, M Model = IPF prediction for males, F Model = IPF predictions for females. The microsimulation uses the 2010 census population composition. Population Projection for Japan: 2011-2060.

Health transitions

Appendix Tables 4 (JSTAR) presents the results of our conditional health transition model for all 19 health dimensions. The coefficients on age are generally

positive, signifying that the probability of onset for various conditions tends to increase with age. Coefficients that are negative are often indistinguishable from 0. Positive coefficients in Appendix Table 4 indicate a higher disease onset probability and thus poorer health. For example, in Appendix Table 4, having hypertension in 2007 increases the probability heart disease onset in 2009. Having a BMI $\geq$ 23.5 in 2009 increases the probability of having diabetes in 2009.

All explanatory covariates are measured with a two-year lag, i.e., as of the first interview of the interview-pair in 2007 relative to the second interview in 2009. Note the very powerful cross-effects of comorbid health conditions. For example, hypertension, hyperlipidemia, diabetes, asthma, liver disease, ulcer, osteoporosis, and "other" diseases all increase the risk of developing heart disease. Heart disease, hyperlipidemia, cerebrovascular disease, diabetes, and liver disease are all correlated with the onset of hypertension. Men tend to have higher risks of cerebrovascular disease, chronic obstructive pulmonary disease, asthma, ulcer, bladder disease and cancer than women, and lower risks of heart disease, hypertension, hyperlipidemia, joint disorder, bone fractures/broken hip, osteoporosis, eye disease, mental health disorders, dementia and skin disease. Being overweight is highly correlated with the onset of hypertension, hyperlipidemia, cerebrovascular disease, diabetes, liver disease broken hip, and joint disorder. Smoking more than 20 cigarettes a day increases the risk of heart disease and diabetes in particular, but does not appear to predict other disease very well. We do not control for a generic "ever smoked" variable because its effects are often contradictory. It is possible that the respondents' answers are particularly inaccurate for this variable. An alternative explanation may be that very high measures of smoking behavior are required to show a health effect in the Japanese context.

Appendix Table 4: JSTAR Health Transition Matrix

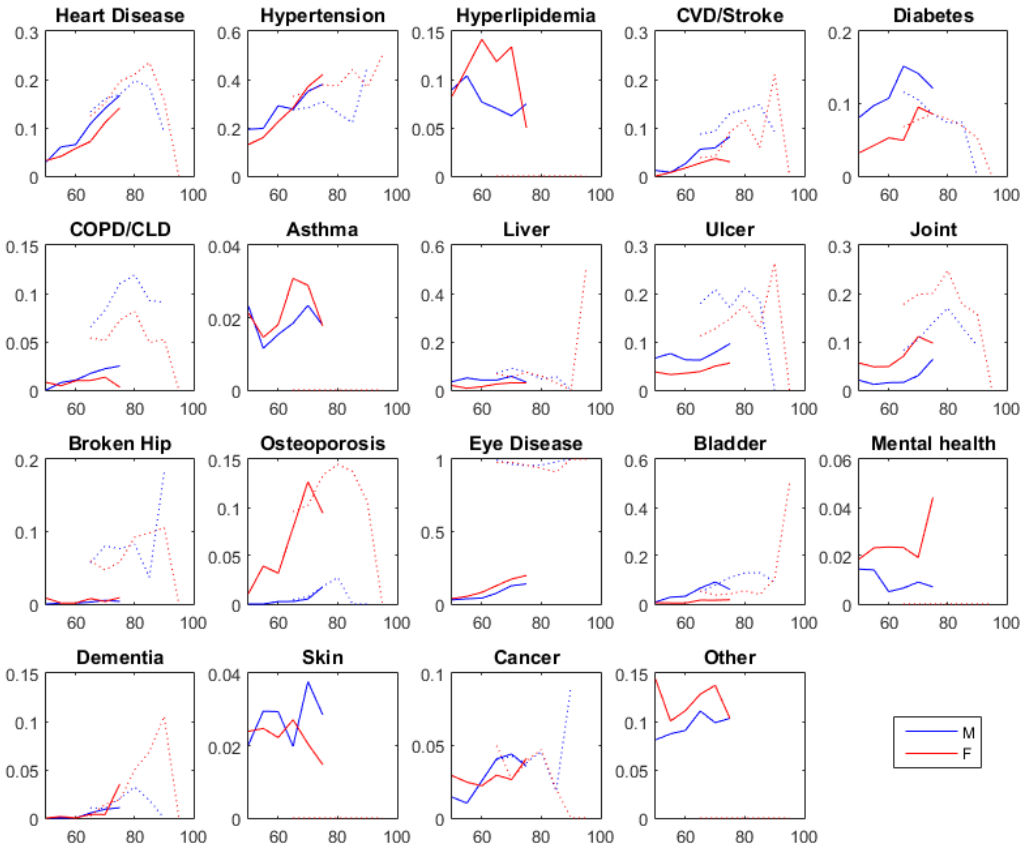
	(1) heart disease 2009	(2) hypertension 2009	(3) hyperlipidemia 2009	(4) CVD 2009	(5) diabetes 2009	(6) COPD 2009	(7) asthma 2009	(8) liver 2009	(9) ulcer 2009	(10) joint 2009	(11) broken hip 2009	(12) osteoporosis 2009	(13) eye disease 2009	(14) bladder disease 2009	(15) mental health 2009	(16) dementia 2009	(17) skin 2009	(18) cancer 2009	(19) other 2009
main																			
age 2007	0.0333	0.0595***	-0.00690	0.100*	0.0121	0.101	0.104*	0.0373	0.0423	0.0387	0.0159	0.0402	0.0666***	0.113***	-0.0195	0.285**	0.00790	0.0106	0.0111
	(0.0251)	(0.0160)	(0.0235)	(0.0412)	(0.0232)	(0.0748)	(0.0473)	(0.0402)	(0.0454)	(0.0268)	(0.0639)	(0.0269)	(0.0182)	(0.0306)	(0.0467)	(0.0915)	(0.0232)	(0.0194)	(0.0161)
male	-0.464	-0.0983	-0.771*	0.655	-0.153	1.756*	0.00653	-0.358	0.357	-0.921*	-0.910	-2.264***	-0.647*	1.203*	-0.930	-0.784	-0.591	0.338	-0.216
	(0.433)	(0.231)	(0.302)	(0.506)	(0.350)	(0.761)	(0.581)	(0.579)	(0.537)	(0.398)	(0.789)	(0.483)	(0.258)	(0.522)	(0.620)	(0.835)	(0.384)	(0.413)	(0.226)
BMI >= 23.5 in 2007		0.802***	0.443	0.577	0.838**			0.338		0.679	0.163	-0.318							
		(0.215)	(0.289)	(0.486)	(0.322)			(0.605)		(0.369)	(0.934)	(0.366)							
smoker 2007	0.518				0.602	0.0889							0.00213						
	(0.431)				(0.388)	(0.626)							(0.324)						
heart disease 2007		0.411				0.876		0.113			1.545*	0.994*	0.673*				0.486		
		(0.288)				(0.756)		(0.657)			(0.716)	(0.415)	(0.284)				(0.519)		
hypertension 2007	0.0390			0.619		0.164		0.605					0.0296						
	(0.379)			(0.462)		(0.905)		(0.543)					(0.238)						
hyperlipidemia 2007	0.352	0.257		-0.122				0.186											
	(0.408)	(0.263)		(0.565)				(0.586)											
CVD 2007		0.584											0.530						
		(0.460)											(0.453)						
diabetes 2007	1.030*	0.00223	0.793*	0.799					0.753				0.844**	0.792					
	(0.426)	(0.311)	(0.365)	(0.560)					(0.523)				(0.280)	(0.462)					
COPD 2007																			0.547
																			(0.537)
asthma 2007	1.078					3.036***		0.871			2.780***								
	(0.642)					(0.590)		(0.816)			(0.800)								
liver 2007	0.878	0.758*		0.791	0.450	2.021***					2.336***		0.477			0.351			
	(0.551)	(0.323)		(0.645)	(0.490)	(0.562)					(0.635)		(0.460)			(1.107)			
ulcer 2007	0.467										1.624*						1.118*		0.0119
	(0.443)										(0.659)						(0.466)		(0.301)
joint 2007								0.816											
								(0.753)											
broken hip 2007												1.978*							1.363
												(0.911)							(0.903)
osteoporosis 2007	0.866						-1.063				1.906								0.497
	(0.608)						(1.360)				(1.133)								(0.385)
eye disease 2007									0.572										
									(0.618)										
bladder disease 2007									-0.101										0.215
									(0.869)										(0.386)
mental health 2007									1.544*							0.360			
									(0.702)							(1.205)			
dementia 2007							3.090**												
							(1.112)												
skin 2007								1.177											
								(0.825)											
cancer 2007								0.808	0.438	-0.146		0.453		0.0996					
								(0.777)	(0.804)	(0.648)		(0.644)		(0.658)					
other 2007	0.299		0.160					1.124*				0.716	0.111				1.048*		
	(0.359)		(0.328)					(0.538)				(0.371)	(0.261)				(0.428)		
Constant	-6.398***	-6.469***	-2.731	-12.22***	-4.649**	-14.32**	-11.66***	-8.221**	-7.529*	-6.301***	-8.655*	-6.334***	-7.186***	-12.33***	-2.873	-24.69***	-5.231**	-5.191***	-2.963**
	(1.548)	(1.065)	(1.573)	(3.019)	(1.485)	(4.613)	(2.965)	(2.684)	(2.955)	(1.825)	(4.392)	(1.657)	(1.187)	(2.040)	(2.999)	(6.497)	(1.746)	(1.433)	(1.036)
Observations	1595	1051	1537	1765	1587	1842	1805	1730	1648	1708	1841	1739	1567	1782	1825	1873	1797	1781	1376
R-squared																			

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Appendix Figure 5 compares the age- and sex-specific disease prevalence rates for the JSTAR and NUJLSOA, for the medical conditions reported in both datasets. Data on hyperlipidemia, asthma, mental health, skin and “other” health conditions are not available in the NUJLSOA. For the most prevalent conditions, the age-specific prevalence rates are reasonably close, with some indication of compression of morbidity for heart disease, stroke, and ulcers (i.e., for the overlapping age cohorts between 65 and 75, the NUJLSOA shows higher prevalence than the more recent JSTAR cohort). Some of the discrepancies reflect different wording of the questions (e.g. for eye disease). These discrepancies should not impact our projections to a large extent because they are mostly confined to conditions that are not leading causes of death. Nevertheless, a consistent source of data for both the elderly and oldest-old populations would improve the ability to make accurate forecasts.

Appendix Figure 5: Comparing disease prevalence between JSTAR (solid lines) and Nihon University Japanese Longitudinal Study of Aging (NUJLSOA) (dashed lines)



Note: Data on hyperlipidemia, asthma, mental health, skin and "other" health conditions are not available in the NUJLSOA.

Disability

The Japanese population surveyed in JSTAR appears to be relatively healthy based on self-reported ADLs, IADLs, and other measures of social and mental functioning. In our data, approximately 95% of respondents report having no difficulty in ADLs, and 3%, 1%, and 2% respectively reporting difficulties in 1, 2, and 3+ ADLs. For IADLs, these figures are respectively 93% (no IADL), 4% (1 IADL), 1% (2 IADLs), and 2% (3+ IADLs). For social activities, 71% reported having no difficulty, followed by 17%, 7%, and 5% respectively for 1, 2, and 3+ difficulties. For intellectual activities, the figures are respectively 78% (no difficulty), 15% (1 difficulty), 5% (2 difficulties), and 3% (3+ difficulties). Finally, of the 6,328 observations with a non-missing response, 8% reported

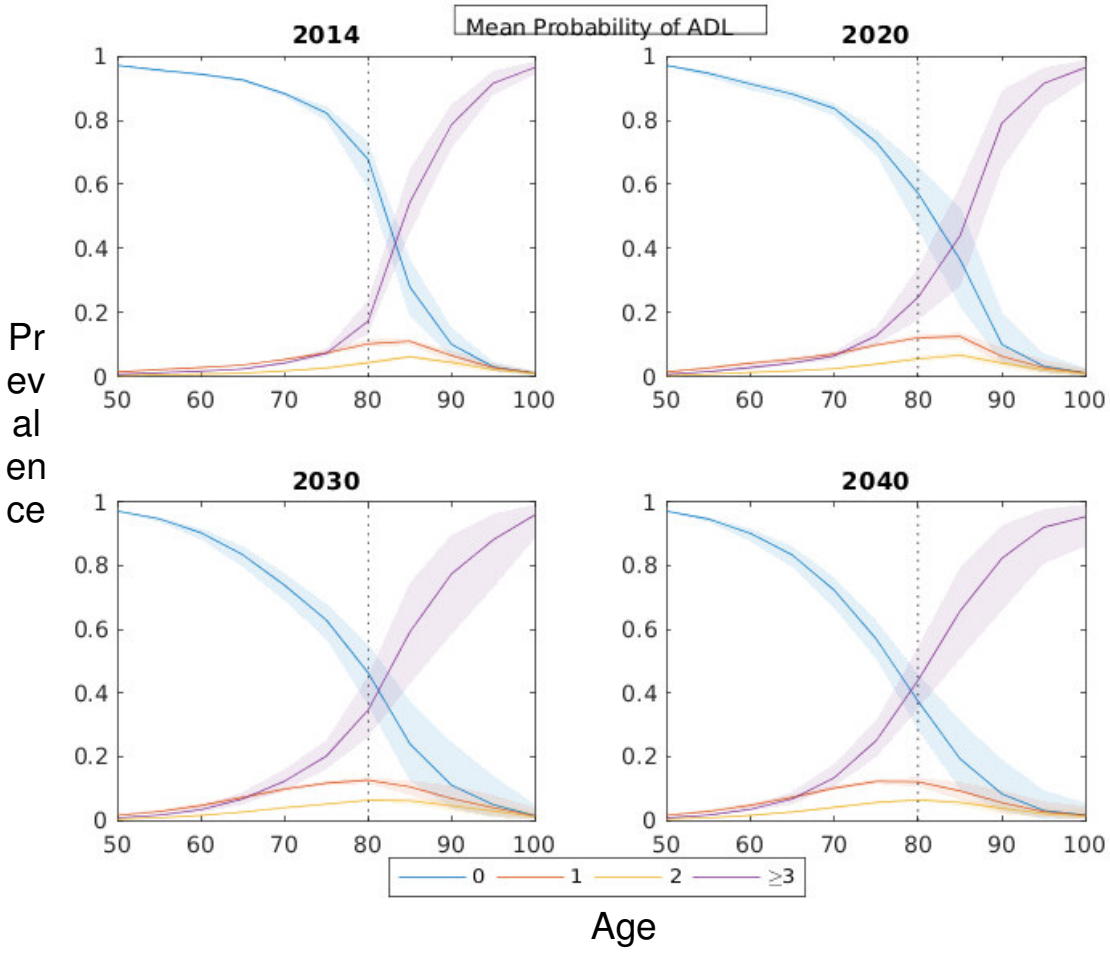
receiving some sort of help from friends and family, while 22% of 523 non-missing responses reported having received some type of physical assistance, and 42% of 520 non-missing responses reported having received assistance for household chores.

The ordered logit regressions and logit regressions show that three chronic illnesses impose the most consistent burden on physical and mental functioning across all measures (ADLs, IADLs, social, intellectual functioning, and care receiving). These illnesses include cerebrovascular disease, diabetes, and dementia; coefficients are particularly large for these three medical conditions (see Appendix Table 5). Other chronic illnesses that adversely impact functioning include heart disease, joint disorder, broken hip, osteoporosis, mental health, and "other" diseases. Joint disorder and broken hip affect ADLs and IADLs in particular, and mental health problems are positively associated with having difficulty with ADLs, IADLs, as well as social and intellectual activities. Older age is also unsurprisingly associated with greater difficulties in physical and mental functioning.

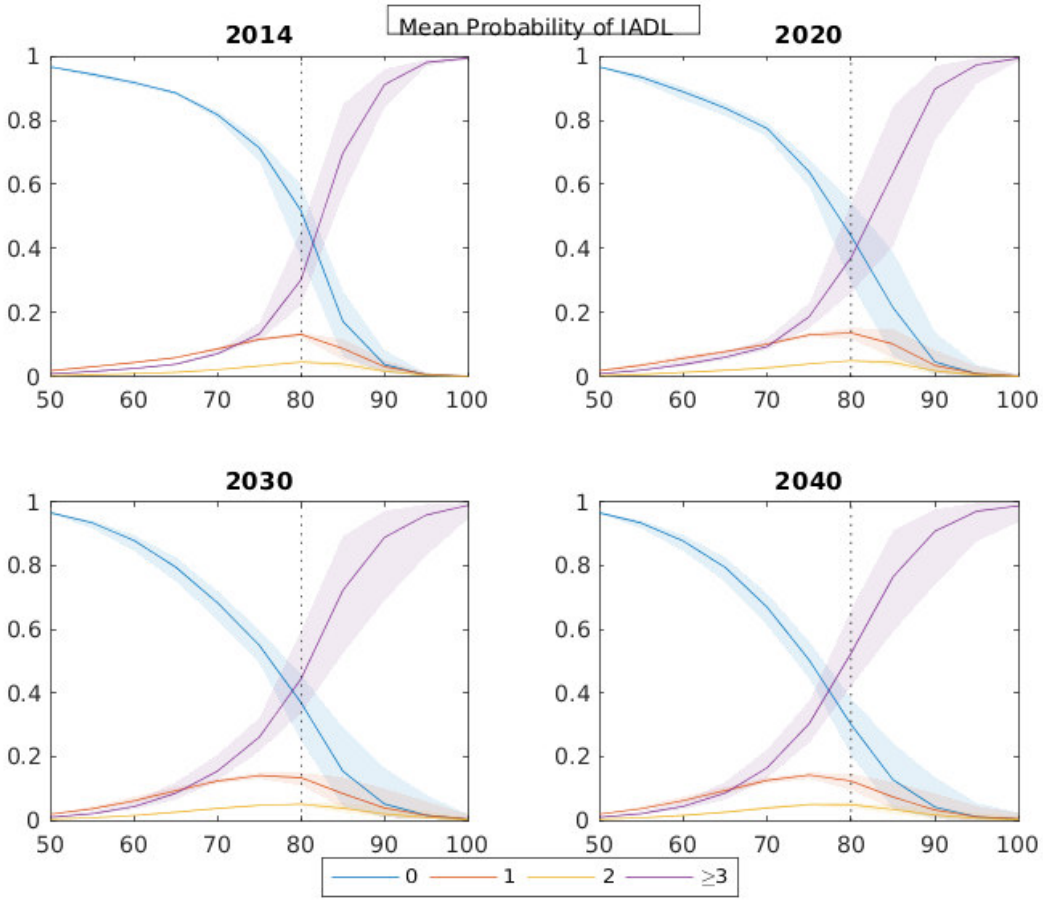
In Appendix Figures 6, 7, and 8, we project how the population with 3 or more disabilities will evolve over the 2014-2040 period. As shown in Appendix Figure 6, the predicted prevalence of no difficulty with activities of daily living decreases sharply with age, and the prevalence of difficulty with 3 or more ADLs increases sharply with age, with only moderate changes in the age pattern of disability by simulation year. Similar patterns arise for IADLs (Appendix Figure 7) as well as for cognitive/intellectual disabilities and social functioning disabilities (not shown). Therefore, the prevalence of disabilities among the future elderly (Appendix Figure 8a) is largely driven by the evolution of the age structure among the 50+ population towards a greater proportion of oldest-old with a larger share of disability, although holding the age distribution constant at the 2010 age distribution reveals that a modest future increase in disability at given age (Appendix Figure 8b).

In these figures, we conduct probabilistic sensitivity analyses given that our transition probabilities are likely to be imprecisely estimated. To do so, we resample our transition matrix coefficients from a multivariate joint normal distribution, using the estimated coefficients and variance-covariance matrices to construct a 95% confidence interval around our simulation results with 50,000 runs.

Appendix Figure 6: ADL Disability Over Time, with 95% CI

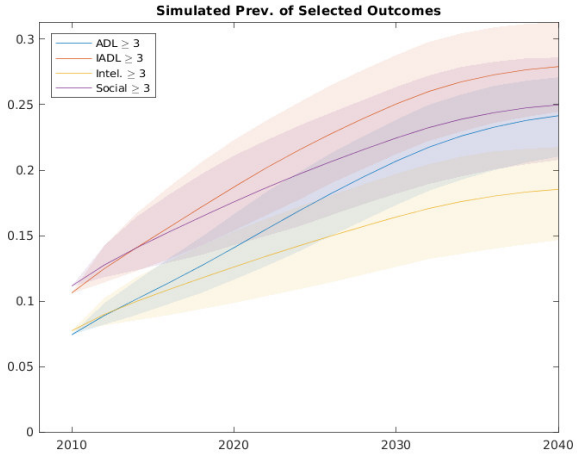


Appendix Figure 7: IADL Disability Over Time, with 95% CI

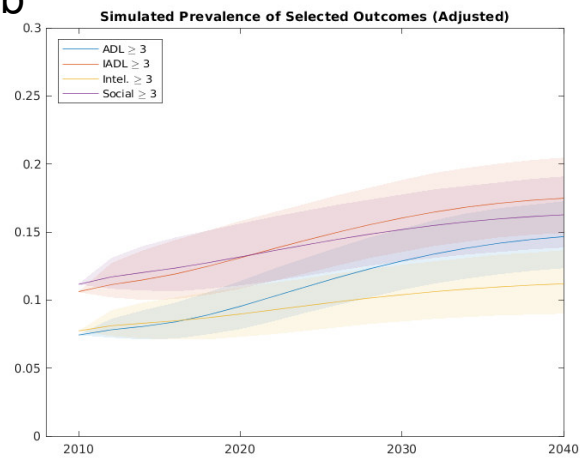


Appendix Figure 8a and 8b: Simulated Prevalence of Selected Outcomes, (a) Unadjusted, and (b) Holding Age Structure Constant at 2010 Levels, with 95% CI

a



b



Appendix Table 5: Transition Matrix for Activities of Daily Living (Ordered Logit) / Care Receiving (Logit)

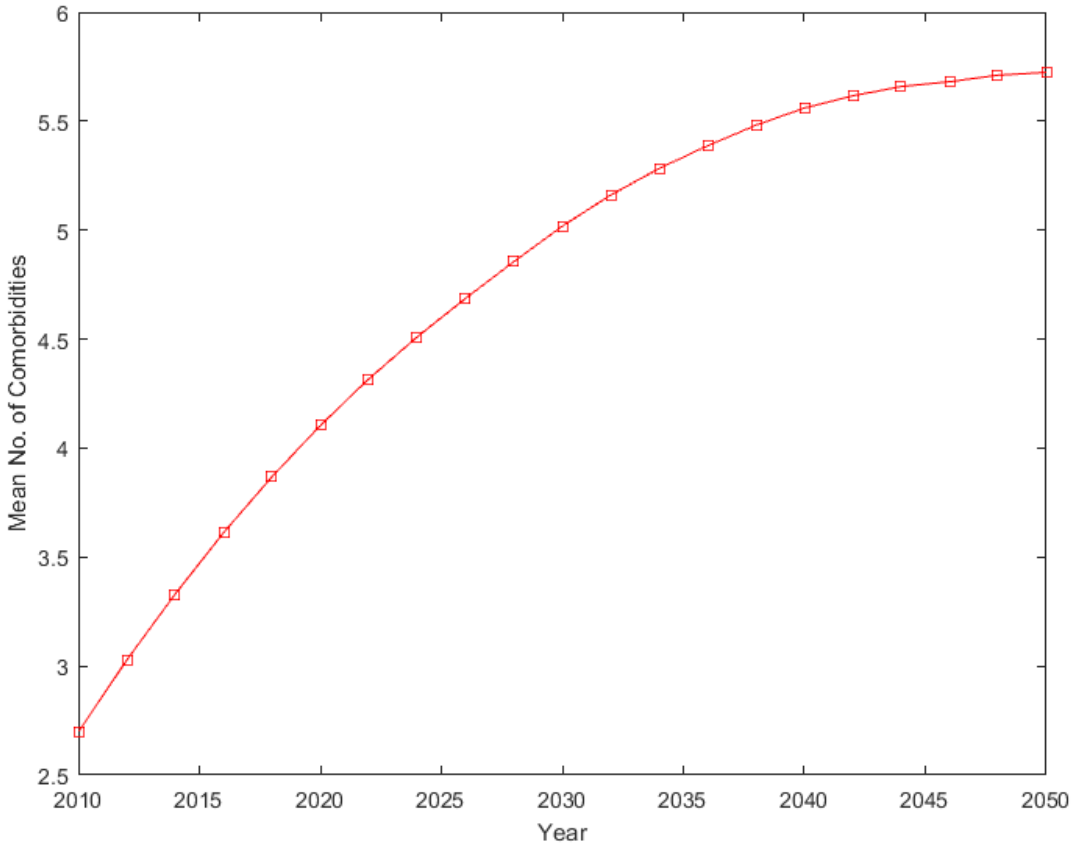
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Activities of Daily Living		Other Activities		Received Help from Friends/Family		
VARIABLES	ADL	IADL	Intellectual	Social	Any Help	Physical Care	Chores
age	-0.0402	-0.160	-0.0629	-0.150	-0.209	0.340	0.217
	(0.244)	(0.193)	(0.111)	(0.0991)	(0.144)	(0.334)	(0.305)
age squared	0.000537	0.00175	0.000640	0.00127*	0.00157	-0.00241	-0.00149
	(0.00187)	(0.00147)	(0.000855)	(0.000768)	(0.00112)	(0.00258)	(0.00234)
male	-0.196	0.361**	0.141	0.505***	-0.401***	0.374	-0.187
	(0.181)	(0.150)	(0.0922)	(0.0816)	(0.117)	(0.280)	(0.268)
BMI >= 23.5	0.0794	-0.116	0.0133	-0.114	-0.183	0.420	-0.140
	(0.168)	(0.132)	(0.0802)	(0.0721)	(0.112)	(0.258)	(0.234)
>= 20 cigarettes/day	-0.0146	0.432***	0.399***	0.0645	-0.0775	-0.891*	0.350
	(0.236)	(0.161)	(0.104)	(0.0951)	(0.174)	(0.477)	(0.360)
heart disease	0.492**	0.282*	0.208*	0.202*	0.0947		
	(0.196)	(0.169)	(0.115)	(0.106)	(0.160)		
hypertension	0.242	0.0503		0.0180	0.0454	0.0960	0.368
	(0.170)	(0.135)		(0.0756)	(0.116)	(0.258)	(0.232)
CVD	1.830***	1.164***	1.137***	0.842***	1.520***	1.231***	0.935**
	(0.253)	(0.251)	(0.173)	(0.186)	(0.199)	(0.328)	(0.379)
diabetes	0.794***	0.860***	0.416***	0.361***	0.466***	0.591*	0.498
	(0.200)	(0.160)	(0.114)	(0.102)	(0.153)	(0.309)	(0.314)
COPD	0.234	0.406		0.221	0.590	0.814	0.699
	(0.572)	(0.416)		(0.297)	(0.421)	(0.696)	(0.670)
asthma	0.185	0.175		0.673***	0.0138	0.560	
	(0.409)	(0.340)		(0.167)	(0.322)	(0.640)	
liver	0.264		0.161	0.164	0.119	0.563	0.282
	(0.326)		(0.171)	(0.164)	(0.240)	(0.449)	(0.468)
ulcer	0.144		0.215*	0.0920	0.148	0.877**	0.851**
	(0.263)		(0.127)	(0.120)	(0.195)	(0.368)	(0.354)
joint	1.387***	0.592***	0.147	0.0743	0.719***		0.885**
	(0.213)	(0.218)	(0.154)	(0.141)	(0.167)		(0.366)
broken hip	1.008*	1.923***		0.659	0.170	0.732	1.283
	(0.538)	(0.442)		(0.564)	(0.668)	(1.142)	(1.324)
osteoporosis	0.437	0.409	0.277*	0.332**			
	(0.300)	(0.264)	(0.165)	(0.152)			
eye disease	0.186		0.0975	0.0148			0.641**
	(0.214)		(0.112)	(0.102)			(0.311)
bladder	0.949***	0.00911	0.0575	0.152			-0.0792
	(0.274)	(0.269)	(0.178)	(0.163)			(0.666)
mental health	1.137***	1.535***	1.205***	0.795***	1.185***		
	(0.312)	(0.329)	(0.248)	(0.260)	(0.220)		
dementia	1.903***	3.027***	2.368***	2.429***	1.824***	1.903***	2.573**
	(0.608)	(0.517)	(0.518)	(0.418)	(0.498)	(0.633)	(1.141)
skin	0.313	0.360	0.0930	0.248	0.597***	-0.0975	0.0467
	(0.311)	(0.289)	(0.179)	(0.176)	(0.230)	(0.568)	(0.458)
cancer	0.496	0.427*			0.261	0.420	0.425
	(0.314)	(0.251)			(0.255)	(0.529)	(0.432)
other	0.683***	0.316**	0.259***	0.218***	0.323***	0.281	0.0145
	(0.166)	(0.145)	(0.0891)	(0.0829)	(0.123)	(0.286)	(0.261)
Constant					4.284	-14.07	-8.591
					(4.568)	(10.69)	(9.841)
/Cut1	3.901	0.535	0.391	-2.909			
	(7.927)	(6.289)	(3.553)	(3.171)			
/Cut2	4.765	1.453	1.698	-1.806			
	(7.932)	(6.287)	(3.557)	(3.169)			
/Cut3	5.226	1.822	2.837	-0.802			
	(7.939)	(6.291)	(3.556)	(3.169)			
Observations	5,124	4,921	4,920	4,917	5,099	439	438

Robust standard errors in p
*** p<0.01, ** p<0.05, * p<0
Statistical analyses: Ordered logit for (1)-(4); logit for (5)-(7)

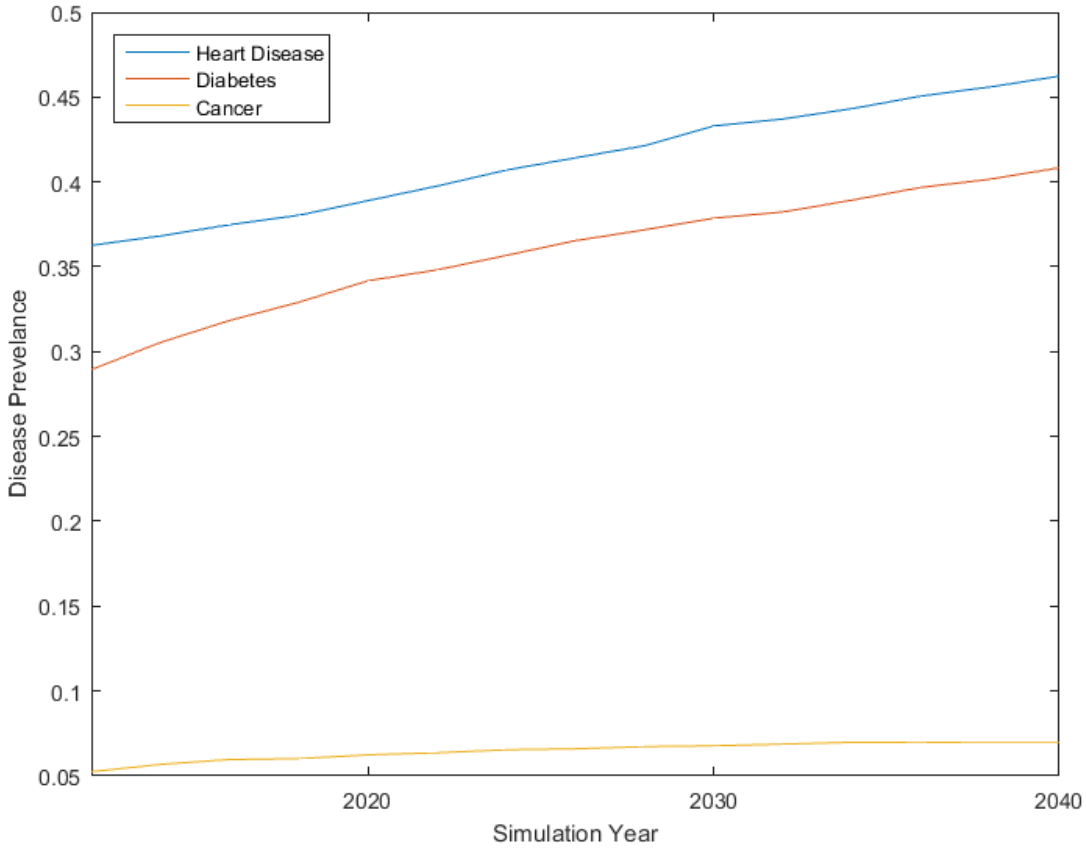
Simulated Prevalence of Diseases

Appendix Figures 9 and 10 show the estimated prevalence of disease for Japan's future population of older adults. The average number of comorbidities per individual is projected to more than double by 2040 (Appendix Figure 9). Appendix Figure 10 summarizes the average population prevalence of heart disease, diabetes, and cancer among the Japanese population age 50 and older. Cancer prevalence remains around 5-7.5% throughout the 30-year period; diabetes prevalence increases from 28% to 37% by 2040; and heart disease prevalence increases from 37% to 47%, indicating that almost half of Japanese aged 50 and older will have heart disease by 2040. Appendix Figure 11 shows greater survival into old age with disability-associated comorbidities, such as joint disease, broken hip, osteoporosis, mental health disorders and dementia.

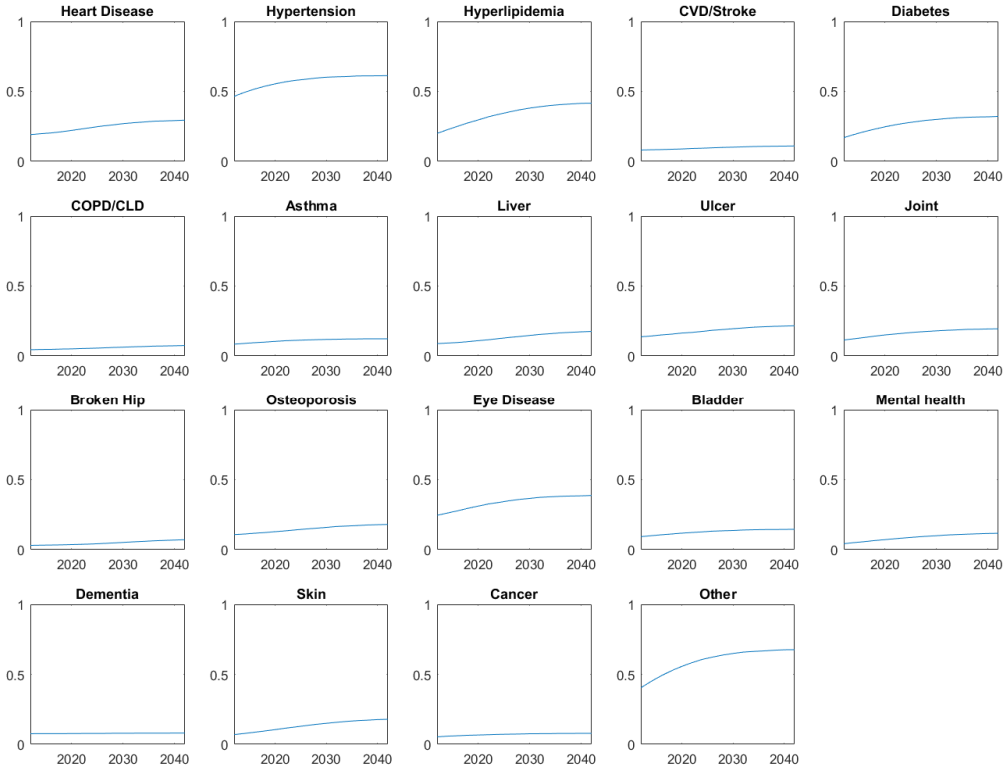
Appendix Figure 9: Average number of comorbidities per individual age 50+



Appendix Figure 10: Projected increase in the prevalence of heart disease, diabetes and cancer among Japan's population aged 50 and older, 2010 - 2040



Appendix Figure 11: Survival with greater disability-associated morbidity



Online Appendix 2: JSTAR Data Limitations

The JSTAR data, although pioneering, also has several limitations, including lack of national representativeness or coverage of the frailest oldest-old population. The JSTAR team emphasized several reasons for their sample selection decision. First, national representative data typically sample a cohort from a few hundred regions with a few dozen individuals for each region. This approach may be more effective in reproducing the "national representative" averages, but potentially insufficient to carry econometric studies that focus on shared cultural contexts within individual municipalities. Second, a response rate of only 15-30% for similar survey efforts is common in Japan. By obtaining a high degree of collaboration from government officials in the five sampled municipalities, JSTAR achieved a response rate of 80%. JSTAR is currently pursuing a strategy of creating sample weights to make the data more reflective of Japan's population as a whole, and in the interim, we have calculated weights by sex and age-group categories that we used probability weights in our health transition regressions.

The JSTAR team compared several key variables from the survey data with the population of each municipality using the Census data. It found that JSTAR represented the population of each municipality well in terms of both marital status and many of the employment statuses for males at a given age. However, the team found that JSTAR did not represent the population of each municipality for educational attainment or employment status among women. While our simulation does not explicitly account for socioeconomic status in any of our transition our outcome models, to the extent that the JSTAR sample is of lower (or higher) socioeconomic status than the average, our results may be respectively over- or understating the prevalence, transition probabilities, and disability probabilities that affect future morbidity and disability – if the association between lower socioeconomic status and poorer health holds in Japan, as it likely does.

Another limitation with the JSTAR dataset is that it lacks observations on individuals over 77 years old. Given our focus on Japan's super-aging future, the lack of the oldest-old group represents a particular shortcoming. However, we partially

addressed this weakness by creating an artificial cohort of 80- to 100-year-olds by aging current 60- to 77-year olds into the future and adding them back to our cohort in 2010. As we show in the Appendix Figure 5, the artificial cohort of our oldest-old aligns reasonably well with actual individuals under 80 in the JSTAR data as of 2010.