添付資料２

Development of micro-simulation model to forecast health and wellbeing in older Japanese

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Abstract
Rapid population aging is regarded as a risk to social sustainability of Japan. Precise estimation of future demand for medical and long-term care in heterogeneous segments of older people is imperative for designing system reform and stability. Currently available future projection, however, simply assumes static and average status of comorbid prevalence and mortality by age and sex. To overcome the limitation, a state-transition multivariable micro-simulation model was developed by following previously developed US Future Elderly Model (FEM), but using Japanese national representative panel data as benchmark reference. Preliminary comparison between estimation and real-world vital statistics confirmed backward validity of our simulation forecast, except for overestimation of cancer death numbers. We discuss potential improvement of the model, and future application of the developed model for policy evaluation.

1. Background

Rapid population aging is regarded as a risk to social sustainability of Japan (Cabinet Office, 2015). Increasing demand for pension support, and medical / long-term care against decreasing support resources threats financial projection of the nation's economy. Population ageing also leads to a considerable disparity among older people in terms of their economic, health, and social resources (Ichimura, et al. 2009). Apparently, precise estimation of future demand for health and social services in heterogeneous segments of older people is imperative to design efficient system reform and stability.

Further challenge to future projection of people's health is that health affects and is affected by socioeconomic conditions (WHO, 2008), and change in life conditions and available health technologies over time leads to change in people's likelihood of health, function, comorbidity and death (Tango, and Kurashina, 1987; Ma, et al. 2007; Wang, et al. 2015). Currently available future projection, however, simply assumes static and average status of comorbid prevalence and mortality by age and sex strata (National Institute of Population and Social Security Research, 2012), fails to incorporate diverse and dynamic associations between health, economy, and social conditions among older people.

One countermeasure to overcome the limitation above has been proposed by Goldman and his colleague economists. Future Elderly Model (FEM) incorporates comprehensive measurement derived from panel data surveys to produce micro-simulation of older people's health, function, mortality, social participation, and economy (Goldman, et al. 2004: Lakdawalla, 2014). The model has been applied to a wide range of policy projection in public health, (Goldman, et al. 2009; Lakdawalla, et al. 2005; Lakdawalla, and Philipson, 2009; Michaud, et al. 2012), healthcare (Bhattacharya, et al. 2005; Lakdawalla, et al. 2009), technology innovation

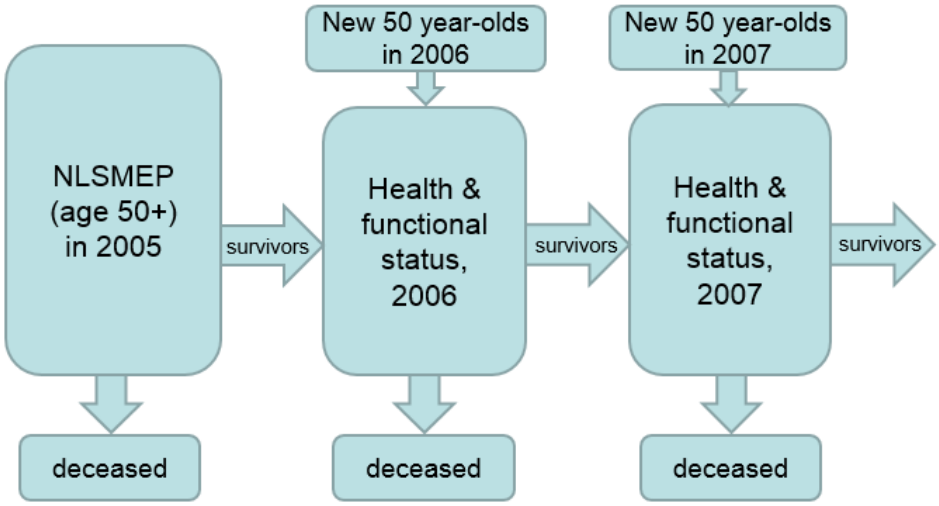
impact (Goldman, et al. 2005), and public finance (Michaud, et al. 2011). Most recently, the model was applied to older population in European and other countries including Japan (Chen, et al. 2016). However, the model development in Japanese context is still in its early stage, and reference data use is limited to a few data source available to US researchers.

In this paper, we report our interim results of developing a version of Japanese FEM with the use of wider set of nationally representative micro data sources to complement previous trials. Our aim to apply nationally representative data source is two folds; to better reflect Japanese demographic and vital status in the projection, and to improve estimation precision to reflect Japanese population in older age.

2. What is FEM

FEM is a Markovian-based multivariate micro-simulation model that consists of three components: health transition module, mortality module, and new cohort module (Figure 1). Health transition module comprises of the probability matrix that reflects disease incidence and transition of individual's multiple comorbidity statuses (horizontal arrows in Fig 1). Mortality module, vertical arrows in Figure1, contains the probability of mortality exit from survivors by accounting for individual's comorbidity status in a previous time period. New cohort module generates a new cohort to newly enter elderly population aged 50 years old and over.

Figure1. Framework of FEM



3. Estimation methods and data sources

3-1. Health transition module

In FEM, the probability of disease incidence is generated by first-order Markov process.

Let H_t denotes a vector of individual's health status at time *t*, and X denotes a vector of demographic characteristics such as birth year, educational status, marital status, and smoking habit in the initial survey year (see Appendix Table1 for included variables). We assumed the probability of disease incidence at the subsequent period H_{t+1}^* follows logistic distribution: for any individual,

$$H^*_{t+1} = H(H_t, X). \quad (1)$$

We defined the individual's health status with comorbid conditions of 6 statuses (heart disease, hypertension, hyperlipidemia, stroke, diabetes, and cancer of any kind) since these conditions are major causes of death and underlying risk factors (Ikeda, et al. 2011). We assumed all health conditions are absorbing states (or once diagnosed, the condition continues until death or attrition):

$$H_{t+1} = \max(\, I(H^*_{t+1} > 0),\ H_t) \quad (2)$$

where I(.) denotes an index function.

To calculate the health transition probabilities, we estimated a random effect logit model separately for each chronic condition. To rewrite equation (1) as

$$H^*_{i,t+1} = \beta'(X_i, a_{i,t}) + \gamma' H_{i,t} + \eta_i + \varepsilon_{i,t} \quad (3)$$

for each individual *i* aged $a_{i,t}$ at time *t*.

We measured demographic characteristics X with gender, educational status, marital status, and smoking habit in the initial survey year. We defined time variant health status with comorbid conditions provided by 6 dichotomous variables. η_i and $\varepsilon_{i,t}$ are unobserved heterogeneity and the error term, respectively. Coefficients β and γ in equation (3) provide transition matrix for calculation of disease incidence.

We excluded individuals who were already diagnosed in the first wave of panel data for each condition to purify transition probability of disease incidence, rather than prevalence.

3-2. Mortality module

In mortality module, we included in the module the probabilities of death from heart disease, cancer, and stroke since they are the 3 main causes of death in Japan. Approximately 65% of deaths among 50s, 60s and 70s population are attributable to these 3 diseases (Health, Labour and Welfare Statistics Association, 2015). Although the original FEM contains more than 10 causes of death, we believe starting with a mortality module with 3 main causes provides a step board for a more extended module. We regarded heart disease (I01-I02.0, I05-I09, I20-I25, I27, I30-I52), cancer (C00-C97), and stroke (I60-I69) coded in International Classification of Death cause version10 (ICD-10).

To build this module, we need to treat competing risks among death causes. For example, an individual with diagnosed conditions of heart disease and stroke in time period t may die of heart disease, stroke, combination of both causes, or other causes of death in the following time period (Figure 2-a). We need to specify competing attribution of death causes to a subpopulation with a certain set of chronic comorbidity conditions.

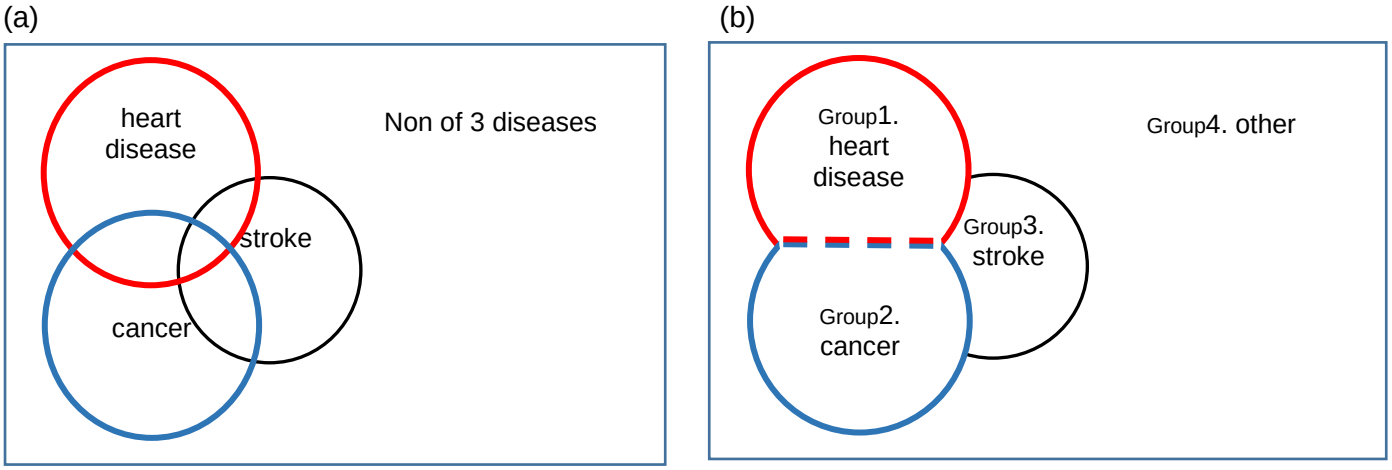
Ideally, vital statistics with multiple causes of death linked with cohort observation of past comorbidity status is the best resource to obtain such multiple attribution of comorbidity and death causes. In reality, such data is very difficult to obtain. Instead, for model simplicity, the original FEM assumes that comorbidity corresponds to a cause of death (e.g. an individual with heart disease will die of heart disease), and that

multiple comorbidity leads to additive probability of mortality from corresponding comorbidity statuses (e.g. mortality of heart disease + mortality of cancer for a case with the two comorbidity statuses).

Since this will lead to upwardly biased mortality, we assumed instead in our model that causes of death are grouped in mutually exclusive manner (Figure 2-b), and each category has a priority cause of death (Table1).

In more details, if comorbidity of heart disease and stroke occurs, we prioritize death from heart disease because heart disease survivors are most likely to die of heart disease, while even stroke survivors would have a 22% chance to die of heart conditions (Bronnum, et al. 2001). We prioritized cancer death when comorbidity of cancer and stroke occurs because cancer patients are most likely to die of cancer, and about 12% of stroke survivors also die of cancer. If comorbidity of heart disease and cancer occurs, we differentially assign death cause according to the time order of comorbidity incidence. We assign death of heart disease in the case that individual was diagnosed with heart disease earlier than with cancer, and vice versa.

Figure2. Venn diagram of disease comorbidity (left) and disjoint groups for assignment to one cause specific mortality (right)



Note: Exterior rectangle (universal set) illustrates the total population. (a) Red, blue, black circles denote groups of patients with heart disease, cancer, and stroke. Comorbidity status is represented intersection of circles. Patients in the intersection of red and blue circles are diagnosed with heart disease and cancer. If people who haven't been diagnosed any of three diseases, they will be located out of circles. (b) To assign a priority cause of death, patients who suffer from multiple diseases will be categorized in one group out of three under mutually exclusive rule in Table1. People who suffer from none of 3 diseases will belong to the fourth group.

Table1. Classification of 4 groups

Group (likely to die from…)	Health condition in the previous year
1. Heart disease	Heart Heart+Stroke

	Heart(earlier incidence)+Cancer Heart(earlier incidence)+Cancer+Stroke
2. Cancer	Cancer Cancer+Stroke Cancer(earlier incidence or coincidence)+Heart Cancer(earlier incidence or coincidence)+Heart+Stroke
3. Stroke	Stroke
4. Other	None of Heart, Cancer, or Stroke

Finally, sex specific mortality rate for age strata by 1 year was obtained as follows. First, we calculated the estimated number of individuals with a set of comorbidity by direct standardization method, using 2005 Census population as a reference population, and the proportion of the corresponding set of comorbidity obtained from social survey datasets we adopted of which details are presented shortly. Then, we obtained the number of mortality case due of culprit causes of death from vital statistic records, following the assumed rules shown in Table 1. Obtained number of cases was divided by the number of individuals with corresponding set of comorbidity to make disease specific mortality rate for each age-sex strata.

3-3. Backward validity check

Using health transition and mortality modules as developed above, we estimated a trend of comorbidity prevalence and cause specific mortality of a virtual closed cohort over a period of time, and compared the estimation results with observed statistics of corresponding age-sex strata in referred survey data for backward validity check of the estimation precision.

Consequently, in this report, we did not treat new cohort module in our simulation, because new cohort module is necessary only in the case of open-cohort assumption that is required for future population projection.[1]

3-4. Data sources

To obtain transition probability of statuses, panel data structure is the most preferred source for the purpose. The Original FEM relied mainly on a nationally representative panel dataset such as The Health and Retirement Study (HRS) and Medicare Beneficiary Survey (MCBS), and complementally used a nationally representative cross-sectional data such as National Health Interview Surveys (NHIS). For mortality modules, they relied on vital statistics records linked with HRS (Goldman, et al. 2009; Lakdawalla, et al. 2009).

Contrarily, Chen et al. (2016) developed a demographic, health and economic state-transition micro-simulation model for Japan adopting the Future Elderly Model (EFM) to forecast trend in disability among Japanese elderly using Japan Study of Aging and Retirement (JSTAR) and Nihon University

[1] New cohort module generates incoming cohort for the subsequent time period. US FEM integrated the joint distribution of demographic and health status of initial 50 year-old population from HRS and health trends among under 50 years old population from NHIS (Goldman, et al. 2004).

Japanese Longitudinal Study of Aging (NUJLSOA). NUJLSOA adopted a probabilistic sample of Japanese aged over 65, while JSTAR adopted probabilistic sample of those aged 50-75 at the baseline in selective municipalities across the nation, and does not provide nationally representative figures.

In this paper, we focused on health transition module and mortality module. We used 8 waves of National Longitudinal Survey of Middle-aged and Elderly People (NLSMEP) and 3 waves of Japanese Study of Ageing and Retirement (JSTAR) for estimation of the probability of disease incidence. We also used a microdata of vital statistics between the period of 2005 and 2012 for estimation of the probability of disease specific mortality. Details of data sources are described in the appendix.

4. Estimation results

4-1. Health transition module

From parameter estimates fitting random effect logit model based on NLSMEP, we obtained the transition matrix A (Table 2). As NLSMEP is annual panel data, the transition matrix A reflects transition of health conditions with 1-year interval.

Random effect assumption was supported by the high values of rho (second row from the bottom in Table2). Age was associated with increased risk of incidence for all diseases. The incidence of heart disease was significantly associated with diabetes, hypertension, and hyperlipidemia that is on par with existing epidemiological evidence. Stroke was also associated with heart disease, but this seems more likely due to their common risk factors.

Incidence of cancer showed associations with all other chronic conditions, which is not well explained by biological mechanism. We interpreted this as a residual confounding by age rather than reflecting underlying biological causes of cancer. Significant prediction of diabetes by preceding heart disease condition may also need careful treatment because it would be rather due to a reverse causation. As such, the estimated probability matrix does not necessarily fit biomedical associations among comorbidity conditions, which is already known in US FEM (Lakdawalla, 2014). Because of this, theoretical adjustment of estimated transition matrix is recommended based on existing medical and epidemiological evidences.

Parameter estimates from JSTAR provided the transition matrix B (Table 3). The transition matrix B transits health conditions with 2-year interval because JSTAR is a 2 year cycled panel data. Matrix B gives us similar patterns as in matrix A.

Table2. Paneled logit estimators for calculation of the probability of disease incidence based on NLSMEP (transition matrix A)

	Diabetes	Heart	Stroke	Hypertension	Hyperlipidemia	Cancer
Male	2.336	1.324	0.586	1.205	-1.582	-0.281
Education	-1.114	0.599	-1.259	0.165	1.699	0.028
Marital	-0.926	-1.268	-0.326	0.125	-1.180	-0.199
Smoke	0.924	1.212	1.027	0.840	0.043	0.616

Age	1.539	0.837	0.699	1.593	1.685	1.025
Diabetes		1.855	1.549	1.487	0.975	0.707
Heart	1.625		2.577	1.654	1.020	0.490
Stroke	0.816	2.453		3.085	0.434	0.739
Hypertension	1.765	2.830	3.679		2.010	0.276
Hyperlipidemia	1.737	1.365	0.986	1.663		0.670
Cancer	0.752	0.783	1.452	-0.087	0.649	
Constant	-112.448	-66.704	-62.039	-107.612	-117.213	-78.274
sigma_u	13.493	8.666	8.635	13.069	18.222	9.622
Rho	0.982	0.958	0.958	0.981	0.990	0.966
Log-likelihood	-13324.4	-10459.7	-6109.4	-24180.2	-24657.4	-9518.4

Note: Sigma_u denotes the standard deviation of the panel-level variance component. Rho measures contribution of the panel-level variance component out of the total variance.

Table3. Paneled logit estimators for calculation of the probability of disease incidence based on JSTAR (transition matrix B)

	Diabetes	Heart	Stroke	Hypertension	hyperlipidemia	Cancer
Male	1.714	1.115	2.653	0.942	-0.769	1.524
Education	-0.732	0.467	-0.591	-0.363	0.571	0.038
Marital	-0.003	0.734	2.242	0.026	0.445	0.837
Smoke	-0.239	-0.421	-0.186	-0.117	-0.523	0.290
Age	0.005	0.164	0.342	0.150	0.021	0.167
Diabetes		0.797	1.340	0.166	0.833	0.387
Heart	0.021		0.526	0.388	-0.318	-1.104
Stroke	1.217	0.289		1.434	0.247	-0.512
Hypertension	1.572	0.762	2.052		0.655	0.297
Hyperlipidemia	1.704	0.962	0.991	1.348		-1.839
Cancer	1.475	-0.149	1.562	-0.235	-0.381	
Constant	-16.455	-24.689	-43.054	-17.193	-8.368	-26.087
sigma_u	7.660	6.168	6.791	5.591	3.668	5.957
Rho	0.947	0.920	0.933	0.905	0.804	0.915
Log-likelihood	-576.2	-539.5	-346.3	-1,194.9	-865.4	-371.2

4-2. Mortality module

We plotted the probabilities of death from heart disease, cancer, stroke, and other causes in Figures 3 and 4. Both NLSMEP and JSTAR suggest the probability of cancer death is much higher than heart disease and stroke for both male and female.

Mortality rate of cancer for male in Figure 3 jumped at 51 years old that seems effect of underdiagnoses in the first wave of NLSMEP. Similar effects can be observed in all 3 diseases for both male and female. Moreover, because very small number of middle aged females experienced stroke, disease specific mortality rate of stroke for females aged 50s looked unstable relative to others. Overall, the mortality rate attributable to heart disease, stroke, and cancer gradually decreased among NLSMEP population for both male and female while Japanese official death rates by cause of death (per 100,000 population) increases among 50s and 60s population (Vital Statistics 2014). We concluded that our disease specific mortality rates

are considerably affected by underdiagnosis of preceding comorbidity conditions.

We extended curves of disease specific mortality rate up to 77 years old using JSTAR. We observed the mortality rate attributable to heart disease, stroke, and cancer increases for both male and female which is consistent with official death rate of Japan.

Fugure3. Disease specific mortality rate based on NLSMEP and vital statistics (50 - 66 years old)

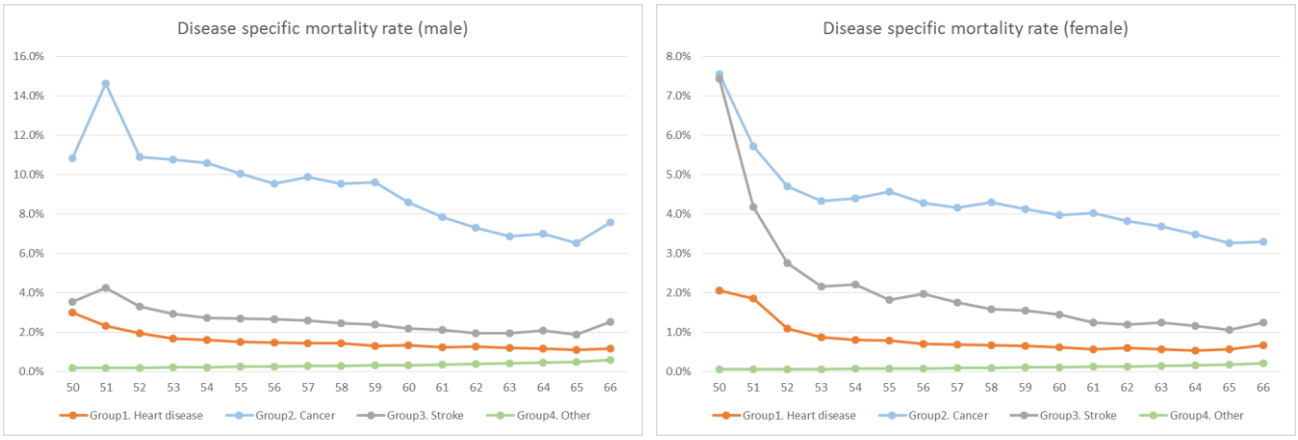
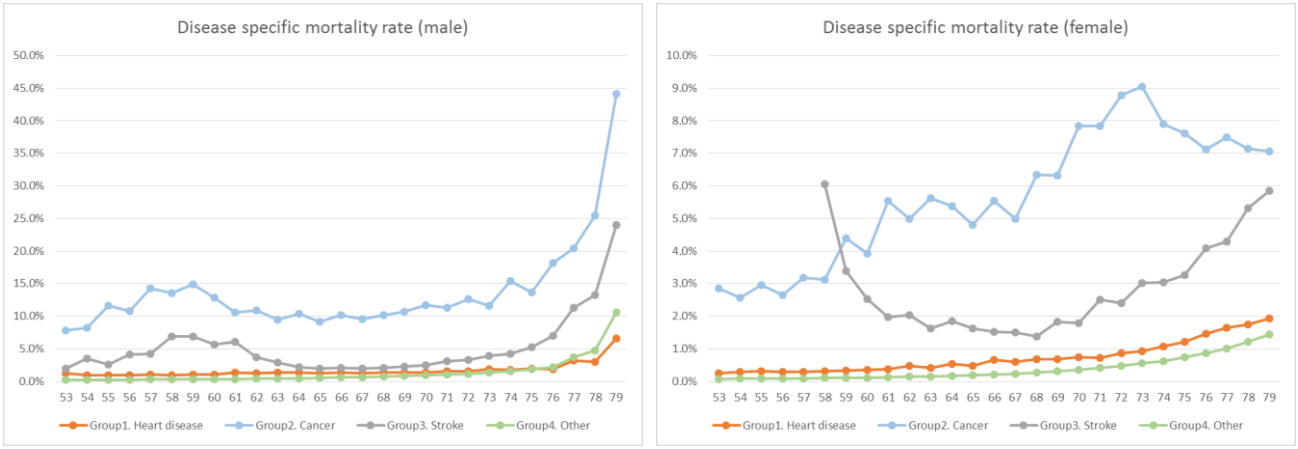


Figure4. Disease specific mortality rate based on JSTAR and vital statistics



4-3. Backward validation check

We assessed our simulation result with backward validation. We started our simulation from year 2005 to compare the results with observed numbers in NLSMEP. First, we executed random sampling by age and gender from 1st wave of NLSMEP with replacement, in order to replicate Japanese population in 2005 between 50 years old and 59 years old, keeping information of age, gender, education, marital status, smoking history, health conditions (heart disease, hypertension, hyperlipidemia, stroke, diabetes, and cancer). Second, 6 health conditions were transited in the individual level from year 2005 to year 2006 by transition module. Third, we categorized individuals into 4 groups by classification in Table 3, and then we assigned them corresponding disease specific mortality rates. At last, probabilistic mortality exists happened

in 2005 population, and then we obtained 2006 population. We repeated the same steps for year 2006 through 2012 (Figure 5).

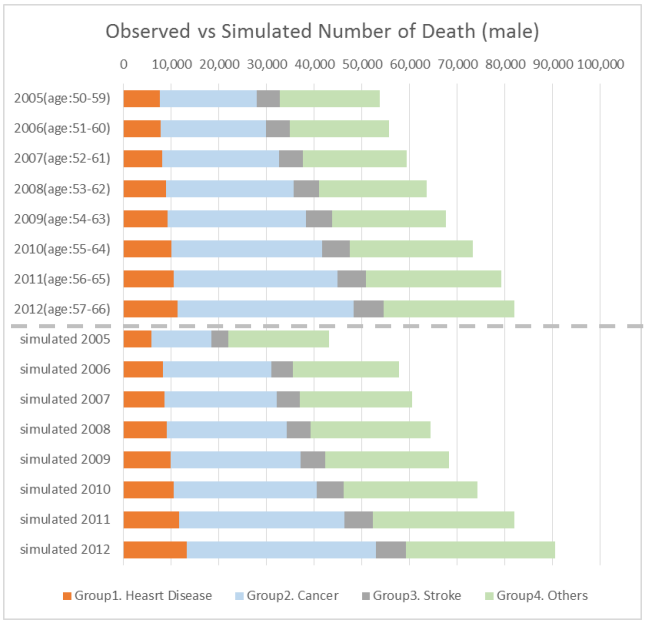
Next, we extended the range of age of our simulation using JSTAR. As JSTAR survey started in 2007, we set the initial population as with 2007 Japanese population. Because the sample size in JSTAR is not sufficiently large, we pooled all 3 waves of JSTAR and took 3 consecutive observations by birth cohort groups. For instance, when we created 53 year old population of 2007 for our simulation, we randomly sampled from observations of 52 years old, 53 years old, and 54 years old in the 1st, 2nd, and 3rd waves. We transited health conditions in 2-year cycle, and we executed mortality module twice before we ran the next transition module.

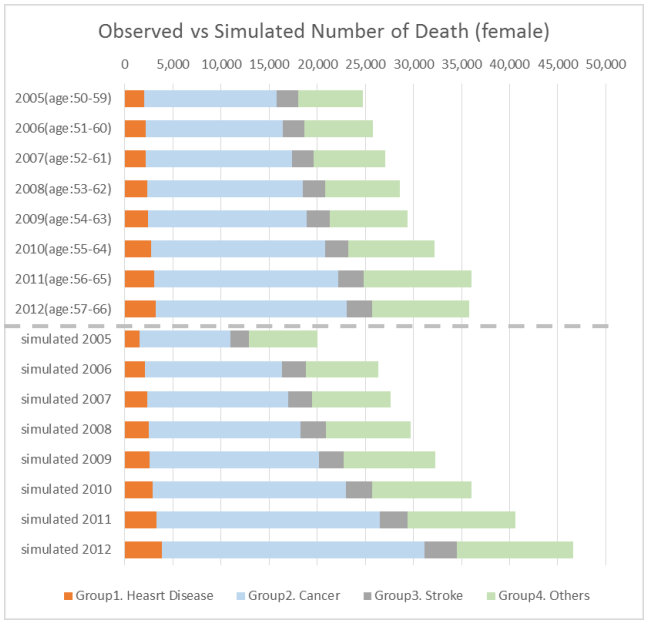
Figures 5 and 6 describe the simulation results based on NLSMEP and vital statistics. Exact numbers in the figures are listed in Appendix Tables 3-6. Our model underestimated the number of mortality in 2005 for both male and female, probably, due to underdiagnosis of comorbidity conditions in the first wave of the panel data. Splitting the results by age (not shown), our model seemed to fit well for the 53-56 age group, however, it underestimated the diseased population for 50-52 age group and overestimated the diseased population for 57-59 age group. The number of cancer deaths in 2012 was overestimated and it was particularly notable for 57-59 age group. JSTAR suggested similar results.

Overestimation of cancer deaths happened partly because our transition matrices may suffer from reverse causal links and confounding bias as we mentioned earlier. Our simulation may need further refinement of matrix elements to better fit biomedical/epidemiological evidence on comorbidity conditions and death causes.

Figure 5. Estimated population from NLSMEP (upper) vs simulated population (lower)

Figure 6. Observed number of death in Vital Statistics (upper) and simulated number of death (lower)





5. Discussion for future study

As our interim results showed, the projection of comorbidity prevalence and cause-specific mortality through developed simulation fairly follows a real-world trend of older people's health status, though it still needs rigorous refinement, especially in mortality module.

In addition to model refinement, extension of coverage over older population is a challenge. NLSMEP and JSTAR do not cover those aged 75 and over, and currently we could not identify suitable panel data source for older age strata. A possible alternative is to use repeated cross-sectional data of national representative survey as pseudo-panel data. For this purpose, National Comprehensive Survey of Living Conditions of People on Health and Welfare (NCSLCPHW), conducted every three years and most latest in 2013, would be suitable.

There are several morbidity and functional conditions that we have failed to include in the module at this stage partly because (i) ADL limitation rarely happens to NLSMEP population (aged 50-66 years old) and (ii) NLSMEP lacks main causal diseases of ADL limitation (e.g. osteo-arthritis, cognitive disease, and so on) except stroke. Since we obtained better projection when we dropped ADL limitation from estimators of transition probabilities, we thought ADL limitation was noise rather than predictor of comorbidity conditions for NLSMEP population for the reason above. However, there might exist other solutions to improve our model (e.g. to exclude reverse causal relationships from the health transition matrix). In the next step, we will attempt to incorporate ADL difficulty, IADL difficulty, and additional health conditions (e.g. dementia, arthritis) from JSTAR. To improve prediction of functional status, we plan to involve socioeconomic status (e.g. currently work or not) as well.

Involving socioeconomic status into the dynamic model will enable us to see complex effects across health and economic outcomes (Shimizutani, et al. 2014; Stowasser, et al. 2011). FEM may be a powerful tool for visualizing wealth-health gradient among population. A challenge will be how to obtain stable estimation with reduced sample size after stratification by socioeconomic status. Bayesian estimation and smoothing

methods would be necessary to be included in the model building.

Despite of these expected challenges, development of Japanese FEM would be a promising endeavor to open new methods of policy evaluation and experimental policy discussion and to deepen our understanding on complex and dynamic health-wellbeing associations among diverse older people in this country.

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Appendix

Data sources

National Longitudinal Survey of Middle-aged and Elderly People (NLSMEP)

National Longitudinal Survey of Middle-aged and Elderly People (NLSMEP) follows a national representative sample of 23 thousand Japanese in age of 50-59 as of 2005 annually. It is still going on and currently 11th wave of NLSMEP was done as of the year 2015. We used 1st through 8th waves for estimation in this study. NLSMEP consists of demographics, 6 comorbid conditions (heart disease, hypertension, hyperlipidemia, stroke, diabetes, and cancer of any kind), functional limitation in activities of daily life, depression (K6 questionnaire), self-reported health, earnings, work status, work classification, retirement age, education, smoking status, marital status, and expenditure (household, medical).

Japanese Study of Ageing and Retirement (JSTAR)

Japanese Study of Ageing and Retirement (JSTAR) covers 3.7 thousand Japanese in age of 50-75 as of 2007 in 5 municipal cities for 3 waves. We extended the range of age cohorts up to 75 years old using JSTAR. As another role, JSTAR reinforces information for ADL, IADL and cognitive function, which are limited in NLSMEP. JSTAR has 19 comorbid conditions and ADL and IADL variables. ADL and mobility questions are verbatim translation from SHARE. IADL measurement in JSTAR is Tokyo Metropolitan Institute of Gerontology Index of IADL, which is most widely used, validated scale of IADL in Japan, overlapping items with IADL measurement in HRS, SHARE, and ELSA (Fujiwara, et al. 2010).

Vital Statistics

Vital Statistics provides individual mortality records with gender, age, and the leading cause of death in ICD-10 code. It is a complete survey for Japanese living in Japan, collected by Ministry of Health, Labour and Welfare. Years 2005 through 2012 are available in the data format. Occupational and industrial information are additionally available in 2005 and 2010, which are the years of Population Census. NLSMEP does not contain mortality exit information, and JSTAR does so only partially. We relied government's vital statistics records to obtain the age-sex specific proportion by leading cause of death between the period of 2005-2012 to reflect trend change of death causes and mortality. We currently consider the probabilities of death from heart disease, cancer, and stroke since they are the three main causes of death in Japan.

Appendix Table1. Definition of variables in NLSMEP and JSTAR

Data source		NLSMEP (aged 50-67)	JSTAR (aged 50-79)
Demographic	Age	Birth year (1945-1955)	Birth year (1930-1957)
	Gender	1: male / 2: female	1: male / 2: female
	Education	1: Middle school 2: High school 3: Vocational school 4: Com colledge 5: University 6: Graduate school 7: Other	1: Elementary/middle school 2: High school 3: Junior college 4: Vocational school 5: University 6: Graduate school (Master's) 7: Graduate school (Ph.D) 8: Other
	marital status	(1st wave) 1: living with his/her spouse 2: separated 3: divorced or widowed 4: never married	(1st wave) marital or common-law partnaer 1: yes (exist) 2: no marital history of the solitary 1: never married 2: widowed 3: divorced 4: don't know 5: refused to answer
	Smoke	(1st wave) 1: currently smoke 2: smoked in the past, but I have quit 3: never smoked regularly	(1st wave) 1: currently smoke 2: smoked in the past, but I have quit 3: never smoked regularly
Health status	heart disease hypertension hyperlipidemia stroke diabetes cancer	1: diagnosed 2: not diagnosed V: unknown or refused to answer	(1st wave) 0: not diagnosed 1: diagnosed (2nd and 3rd waves) 1: newly diagnosed 2: fully recovered once but recurred in the past 2 years 3: still be treated 4: fully recovered / never diagnosed
ADL limitation	walk get up	0: no problem 1: having difficulty but no help 2: needing someone's help	1: yes (has difficulty) 2: no

	dress feed toilet bath		

Appendix Table2. Variable creation for paneled logit models

Panel estimator	Transition matrix A	Transition matrix B
Data source	NLSMEP (aged 50-67)	JSTAR (aged 50-79)
Sample size	n=30,837	n= 10,071
Gender	1: male 0: female (mean: 0.48)	1: male 0: female (mean: 0.50)
Education	1: college education or higher 0: otherwise (mean: 0.16)	1: college education or higher 0: otherwise (mean: 0.12)
Marital status	1: married as of the 1st wave 0: otherwise (mean: 0.87)	1: married as of the 1st wave 0: otherwise (mean: 0.82)
Smoke	1: ever smoke as of 1st wave 0: otherwise (mean: 0.51)	1: ever smoke as of 1st wave 0: otherwise (mean: 0.46)
Health status (Note)	1: newly diagnosed or diagnosed at least once in the past 0: otherwise	1: newly diagnosed or diagnosed at least once in the past 0: otherwise
ADL limitation	1: needing at least one help 0: otherwise	1: having at least one difficulty 0: otherwise

Note: (i) For NLSMEP, we interpolated health status by the previous answer when the respondents refused to answer. For instance, if a respondent answered he/she was never diagnosed as a cancer patient ("2: not diagnosed") in the 1st wave, refused to answer ("V: unknown or refused to answer") in the 2nd and 3rd waves, and "1: diagnosed" in the 4th wave, then we indicated "0: otherwise" in the 1st, 2nd, and 3rd waves, and "1: newly diagnosed or diagnosed at least once in the past" in the 4th wave.
(ii) For JSTAR, when the respondents chose "1:Newly diagnosed with or indicated", "2:Fully recovered once but recurred in the past 2 years", or "3: Still be treated" in the 2nd and 3rd waves, we indicated "1: newly diagnosed or diagnosed at least. "

Appendix Table 3. Estimated population from NLSMEP vs simulated population (male)

Male	Group1. Heasrt Disease		Group2. Cancer		Group3. Stroke		Group4. Others	
Year	observed	simulated	observed	simulated	observed	simulated	observed	Simulated
2005(age:50-59)	328,106	331,422	129,224	122,340	126,319	122,502	8,876,960	8,884,345
2006(age:51-60)	463,782	500,505	178,856	233,992	161,184	170,813	8,605,037	8,512,158
2007(age:52-61)	561,239	566,839	235,407	251,596	200,354	187,215	8,354,178	8,353,976
2008(age:53-62)	650,474	624,062	283,104	273,923	234,149	199,284	8,124,015	8,201,809
2009(age:54-63)	721,280	693,029	351,767	304,053	265,097	214,243	7,890,073	8,023,364
2010(age:55-64)	808,803	776,422	413,949	342,952	279,494	232,366	7,658,975	7,814,639
2011(age:56-65)	883,616	876,527	485,947	392,159	301,833	253,390	7,417,325	7,570,139
2012(age:57-66)	981,198	993,832	572,821	449,614	313,260	277,396	7,141,650	7,289,449

Appendix Table 4. Estimated population from NLSMEP vs simulated population (female)

Female	Group1. Heasrt Disease		Group2. Cancer		Group3. Stroke		Group4. Others	
Year	observed	simulated	observed	simulated	observed	simulated	observed	Simulated
2005(age:50-59)	162,760	156,623	197,402	193,685	74,288	72,369	9,156,604	9,168,377
2006(age:51-60)	235,910	249,869	249,531	308,944	104,211	110,526	8,977,215	8,901,713
2007(age:52-61)	307,375	291,038	311,566	335,546	128,797	125,008	8,794,030	8,793,087
2008(age:53-62)	363,130	328,775	361,743	367,893	149,713	136,662	8,639,562	8,683,756
2009(age:54-63)	420,480	375,576	412,831	409,542	169,864	151,113	8,481,739	8,551,128
2010(age:55-64)	466,828	433,018	489,271	461,257	188,135	169,310	8,311,325	8,391,536
2011(age:56-65)	537,177	503,724	571,494	524,088	205,061	190,622	8,109,659	8,200,685
2012(age:57-66)	604,388	588,847	686,342	599,038	232,806	215,745	7,863,802	7,974,911

Appendix Table 5. Observed number of death in Vital Statistics and simulated number of death (male)

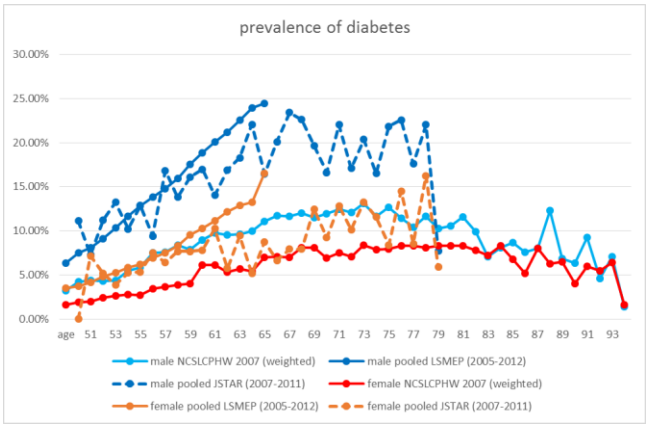
Male	Group1. Heasrt Disease		Group2. Cancer		Group3. Stroke		Group4. Others	
Year	observed	simulated	Observed	simulated	observed	Simulated	observed	Simulated
2005(age:50-59)	7,601	5,872	20,299	12,526	4,841	3,548	20,957	21,195
2006(age:51-60)	7,771	8,172	22,034	22,823	5,008	4,588	20,920	22,259
2007(age:52-61)	8,042	8,636	24,480	23,536	5,072	4,860	21,842	23,516
2008(age:53-62)	8,958	9,063	26,635	25,111	5,386	5,090	22,546	25,125
2009(age:54-63)	9,245	9,836	28,962	27,325	5,587	5,107	23,868	26,042
2010(age:55-64)	9,993	10,508	31,583	29,950	5,947	5,618	25,699	28,088
2011(age:56-65)	10,509	11,589	34,434	34,705	5,931	5,938	28,287	29,692
2012(age:57-66)	11,262	13,222	37,030	39,682	6,262	6,373	27,471	31,178

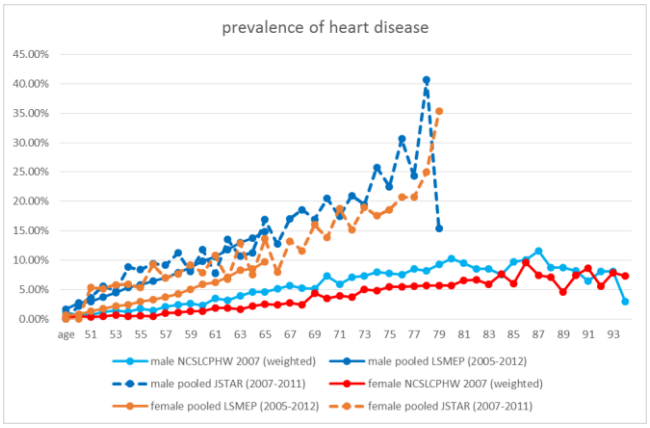
Appendix Table 6. Observed number of death in Vital Statistics and simulated number of death (female)

Female	Group1. Heasrt Disease		Group2. Cancer		Group3. Stroke		Group4. Others	
Year	observed	simulated	observed	simulated	observed	simulated	observed	Simulated
2005(age:50-59)	2,045	1,501	13,735	9,499	2,223	1,864	6,778	7,138
2006(age:51-60)	2,136	2,090	14,269	14,272	2,264	2,467	7,089	7,544
2007(age:52-61)	2,146	2,354	15,244	14,658	2,209	2,447	7,431	8,134
2008(age:53-62)	2,353	2,487	16,175	15,805	2,332	2,613	7,712	8,822
2009(age:54-63)	2,416	2,598	16,485	17,589	2,435	2,539	8,019	9,512
2010(age:55-64)	2,741	2,901	18,113	20,062	2,393	2,731	8,921	10,308
2011(age:56-65)	3,039	3,269	19,161	23,219	2,588	2,934	11,264	11,156
2012(age:57-66)	3,204	3,843	19,861	27,333	2,603	3,297	10,137	12,107

Appendix Figure1. Comparison of disease prevalence by age and gender among LSMEP, JSTAR, and NCSLCPHW

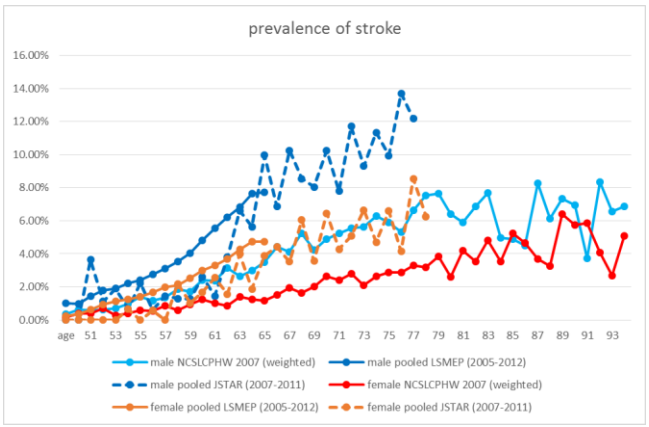
(a) diabetes (b) heart disease

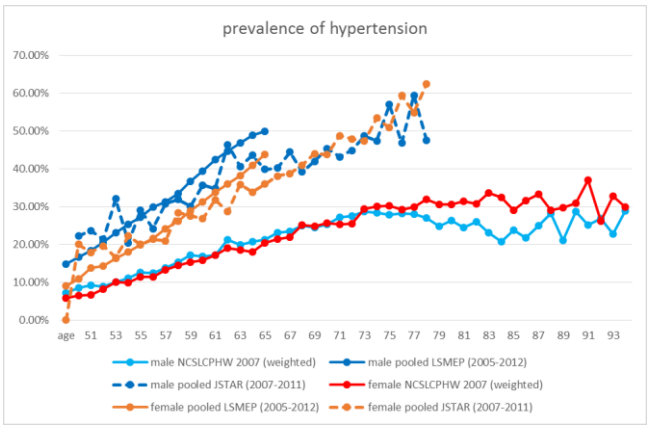




(c) stroke

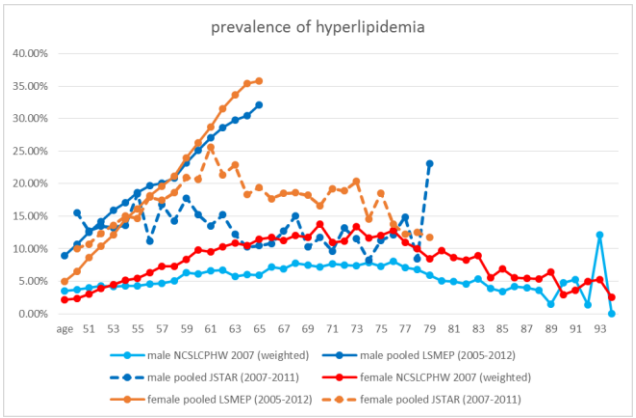
(d) hypertension

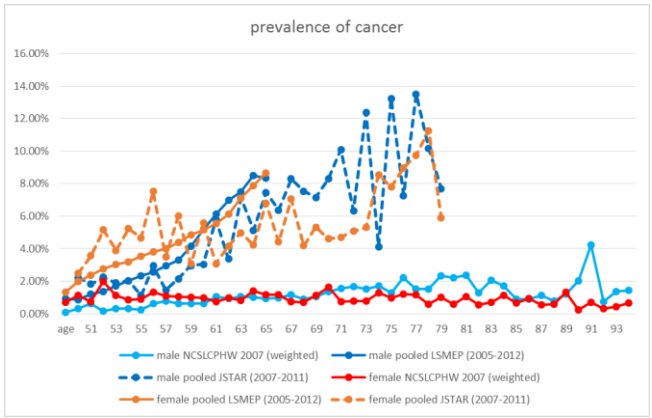




(e) hyperlipidemia

(f) cancer





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