Online Appendix for "Medical Expenditures over the Life-cycle: Persistent Risks and Insurance"

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1 More Details of the NDB Data

This section provides more detailed analysis of the NDB data, which is not covered in Fukai et al. (2022).

1.1 Life-cycle Profiles: NDB and National Data

To demonstrate the comprehensiveness of the NDB, Figure 1 shows that the life-cycle profiles of medical expenditures are in line with the national data reported by the Ministry of Health, Labour and Welfare.[1] As discussed in the data section of Fukai et al. (2022), there are differences in covered items between the NDBs and the national medical expenses, which explains the difference in the two profiles.

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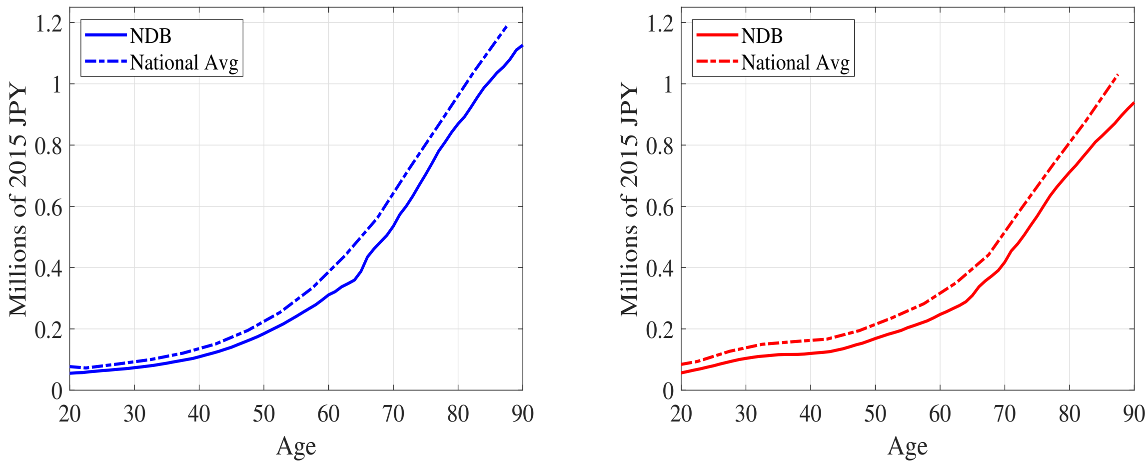
[1]The data is from the Estimates of National Medical Care Expenditure in 2015.
https://www.mhlw.go.jp/toukei/list/37-21.html (in Japanese)
https://www.mhlw.go.jp/english/database/db-hss/enmce.html (in English)



(a) Men

(b) Women

Figure 1: Annual Medical Expenditures: NDB and National Data

1.2 Persistence of Medical Expenditures

Tables 1 and 2 reproduce Tables 1 and 2 in the paper but includes data for women as well. Figure 2 shows probabilities of transiting from bad current health status h_t at time t to either excellent or bad health status in the next period, h_{t+1}, conditional on the health status of the previous period, h_{t-1}. As discussed in the paper, medical expenditure processes are highly persistent and the persistence goes beyond the first order, for both men and women and across all age groups.

Table 1: Health Status Transition $h_t \to h_{t+1}$: M(1), Samples of Age 50, Men and Women

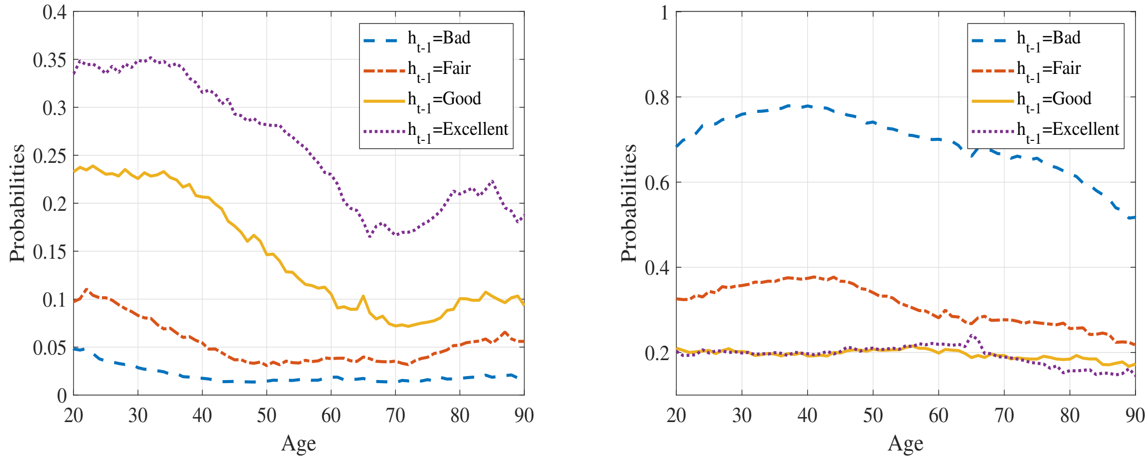
	Health status in $t+1$					
Men	Excellent	Good	Fair	Bad	Death	Total
Excellent	0.778	0.178	0.029	0.014	0.001	1.000
Good	0.317	0.544	0.115	0.023	0.001	1.000
Fair	0.076	0.275	0.579	0.069	0.001	1.000
Bad	0.073	0.121	0.277	0.512	0.017	1.000
	Health status in $t+1$					
Women	Excellent	Good	Fair	Bad	Death	Total
Excellent	0.765	0.192	0.029	0.014	0.000	1.000
Good	0.336	0.513	0.126	0.024	0.000	1.000
Fair	0.079	0.291	0.557	0.073	0.001	1.000
Bad	0.084	0.127	0.276	0.497	0.016	1.000

Table 2: Transition from Bad Health: M(1) and M(2), Samples of Age 50, Men and Women

	Health status in $t+1$					
Men	Excellent	Good	Fair	Bad	Death	Total
M(1)	0.073	0.121	0.277	0.512	0.017	1.000
M(2) by h_{t-1}						
Excellent	0.282	0.256	0.234	0.210	0.019	1.000
Good	0.146	0.327	0.306	0.208	0.013	1.000
Fair	0.031	0.124	0.496	0.340	0.009	1.000
Bad	0.015	0.030	0.193	0.741	0.021	1.000
	Health status in $t+1$					
Women	Excellent	Good	Fair	Bad	Death	Total
M(1)	0.084	0.127	0.276	0.497	0.016	1.000
M(2) by h_{t-1}						
Excellent	0.281	0.248	0.220	0.237	0.014	1.000
Good	0.189	0.322	0.277	0.203	0.010	1.000
Fair	0.055	0.136	0.463	0.339	0.007	1.000
Bad	0.014	0.034	0.210	0.721	0.021	1.000

As shown in Figure 2a, if an individual was in excellent health at time $t-1$, even though he is in bad health at t, he is much more likely to be in excellent health at $t+1$, than those who have been in bad health for more than one period. Figure 2b shows that the probability of staying in bad health in the next period at $t+1$ is significantly higher for those who were in bad health at $t-1$ across all age groups.[2]

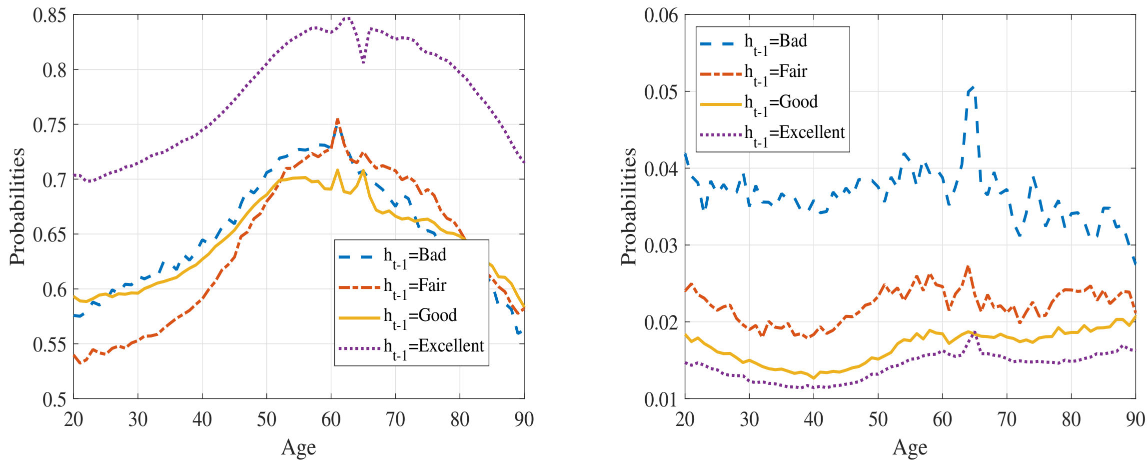
[2]Note that probabilities of the four health status do not sum to 1 since there are individuals who die at $t+1$.



(a) Bad (h_t) to Excellent (h_{t+1}) (b) Bad (h_t) to Bad (h_{t+1})

Figure 2: Transition Probabilities of Health Status *from Bad Health* at t

It is not only bad health but also good health that is persistent beyond the first order. Figure 3 shows probabilities of transiting from excellent health status at time t to either excellent or bad health status in the next period at $t+1$, by health status of the previous period, at time $t-1$. The figures indicate that it is important to consider a higher-order persistence of medical expenditure shocks over the life-cycle among both very healthy and unhealthy individuals.



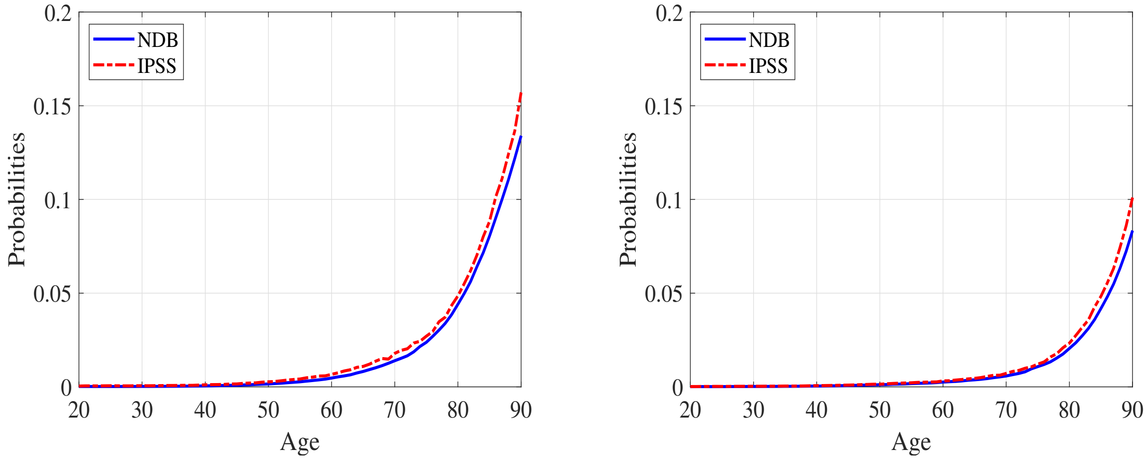
(a) Excellent (h_t) to Excellent (h_{t+1}) (b) Excellent (h_t) to Bad (h_{t+1})

Figure 3: Transition Probabilities of Health Status *from Excellent Health* at t

1.3 Mortality Risks and Health Expenditures

As discussed in the paper, we use the NDB data to identify individuals who pass away in a given period and compute mortality risks by age and gender, and incorporate them in the structural model. In this section, we first show that our estimated mortality risks are in line with those of the National Institute of Population and Social Security Research (IPSS). We then compare the distributions of lifetime medical expenditures when mortality risks are assumed to be independent of health status.

Mortality Risks of the NDB and the IPSS: Figure 4 shows the probability that individuals do not survive until the next year by age and compares the outcome of the NDB with that reported in the national data of the IPSS. The profiles are in line with each other, but note that the death probabilities of the NDB are slightly lower since, as discussed in the paper, the NDB includes only samples of individuals who use medical services and file claims and does not include individuals who never use services covered by national health insurance. For example, it does not include those who remain and pass away at home or in other facilities whose service fees are not covered by the national insurance.



(a) Men

(b) Women

Figure 4: Death Probabilities of the NDB and the IPSS

Health-Dependence of Mortality Risks and Lifetime Medical Expenditures: In this section, we study how health-dependence of mortality risks affect the distribution of lifetime medical expenditures. As discussed in the paper, death probabilities vary not only by age, but also by health status. Although bad health is highly persistent and expenditures accumulate to a large amount, it also comes with high mortality risks, which lowers the effects of bad health on total lifetime expenditures, since expenditures are zero after death.

To isolate effects of health dependence, we simulate lifetime expenditures of many individuals, assuming that mortality risks are independent of health status and depend only on age and gender, based on the unconditional mortality risks of the NDB. Table 3 summarizes moments under the baseline M(2) process and the alternative M(2) with health-independent mortality risks, indicated as Exp. in the second and fourth columns for men and women, respectively.

Table 3: Lifetime Medical Expenditures: Health-dependence of Mortality Risks

	Men		Women	
	Base	Exp.	Base	Exp.
Mean	20.5	22.5	21.4	22.6
Std. dev.	10.9	16.3	10.2	13.5
Coeff. of var.	0.53	0.72	0.48	0.60
Skewness	1.49	1.98	1.43	1.74
% below JPY 10 mm	12.9	19.6	7.9	12.4
% above JPY 40 mm	5.6	11.8	5.4	9.7

Note: Mean and standard deviation are in millions of 2015 JPY.

Total expenditures would be estimated to be higher if mortality risks are assumed to be independent of health status. More individuals with high-risk and expenditures survive longer. Moreover, healthier individuals who survive long in the baseline M(2) are assumed to die sooner in the counterfactual experiment. Risks are much larger as well, and the coefficients of variation would be 0.72 and 0.60 for men and women, respectively, under the experiment and they are much higher than 0.53 and 0.48 in the baseline model. As shown in the last two rows of Table 3, there would be many more individuals in the lower and upper tails of the distribution under the experiment.

1.4 Medical Expenditures in the Year of Death

Expenditures incurred during the final year of life tend to be very high with intensive medical treatments. Figure 5 shows average expenditures during the year of death by age. These are taken into account when computing lifetime medical expenditures in this section.

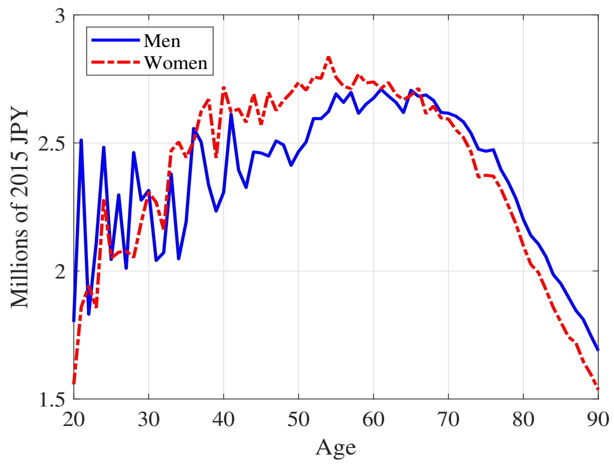


Figure 5: Medical Expenditures in the Year of Death

1.5 More on Lifetime Medical Expenditures

To quantify and visualize the tails of the distribution of lifetime medical expenditures, Table 4 reports distribution over a fixed range of expenditures under the four specifications and Figure 6 shows probability distribution.[3]

The second-order Markov process would imply the largest fraction of population in the group with the lowest lifetime expenditures of less than 10 million yen, as well a group with the largest expenditures of above 40 million yen. Using a first-order Markov process, for example, the probabilities of being in these extreme groups decline, and one would underestimate the variation of lifetime expenditures at both low and high ends of the distribution.

Table 4: Distribution of Lifetime Medical Expenditures (%)

	Men				Women			
	M(2)	M(1)	iid	det.	M(2)	M(1)	iid	det.
$\leq$ 10m JPY	12.9	11.2	8.0	8.4	7.9	6.7	4.9	5.3
$\leq$ 20m JPY	44.0	42.2	30.3	32.1	44.8	42.2	35.6	28.0
$\leq$ 30m JPY	27.4	30.6	41.3	57.3	30.9	34.8	49.0	66.7
$\leq$ 40m JPY	10.1	11.7	10.6	2.2	10.9	12.4	10.0	0.0
$>$ 40m JPY	5.6	4.4	0.8	0.0	5.4	3.9	0.5	0.0
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

[3] A deterministic case is not included in the figure since the distribution depends only on the timing of death and is very non-smooth with high peaks.

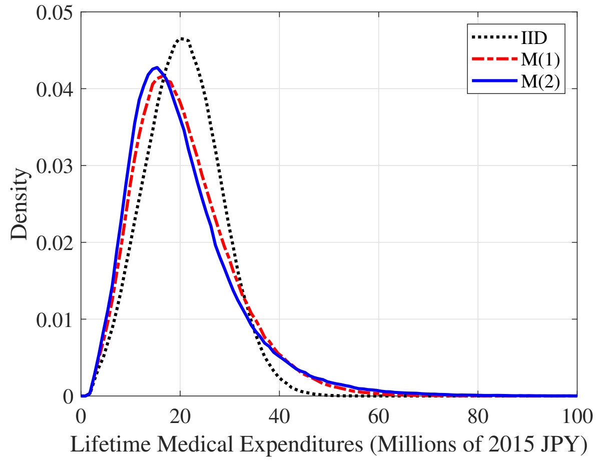


Figure 6: Probability distribution of Lifetime Medical Expenditures under Alternative Processes (Men)

Note: The horizontal axis indicates simulated lifetime medical expenditures in millions of 2015 JPY.

1.6 Lifetime "Out-of-pocket" Medical Expenditures

In this section, we take into account the details of Japan's health insurance program and simulate lifetime out-of-pocket (OOP) medical expenditure process across individuals. Lifetime OOP expenditures are not a simple linear transformation of gross expenditures since copay rates depends on age as well as income and expenditure levels of each individual.

Age-dependent Copay Rates and High-Cost Medical Expense (HCME) Benefits: Based on gross expenditures computed from the NDB, we compute OOP expenditures based on age-dependent copay rates, 30% for adults aged 69 and below, 20% for 70-74 and 10% for 75 and above. OOP expenditures are further adjusted according to High-Cost Medical Expense (HCME) benefits. The maximum copay set by HCME depends on age and annual earnings of each individual. We compute earnings of individuals for each age and gender using the Employment Status Survey (ESS). Using the second order Markov transition matrices of expenditures we computed in Fukai et al. (2022), we simulate lifetime OOP expenditures of many individuals and compute various moments.

Figure 7 compares probability distribution of lifetime gross and OOP medical expenditures. OOP expenditures are significantly lower than gross expenditures and almost no one pays above 15 million yen, with a peak at around 2.5 million.

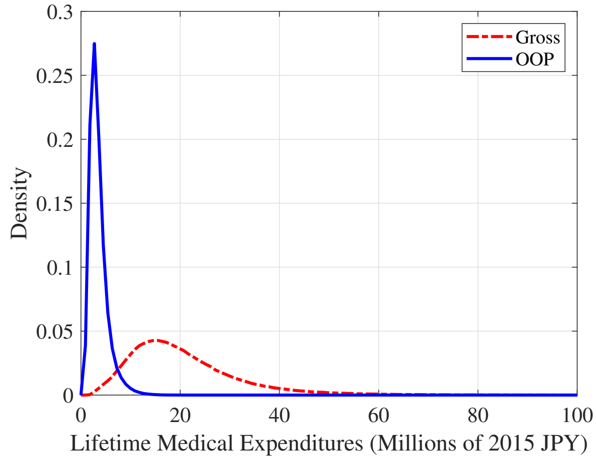


Figure 7: Probability Distribution of Lifetime Medical Expenditures (Men): Gross and Out-of-pocket

Note: The horizontal axis indicates simulated lifetime medical expenditures (gross or out-of-pocket) in million JPY.

Age-dependent copay rates provide significant insurance since coverage rates are high when individuals are old and are more likely to face not only high average expenditures but a large risk of incurring extremely high expenditures. On top of the age-dependent copay rates, HCME benefits provide additional insurance by imposing a ceiling on OOP and providing individuals with a shield against shocks that involve catastrophic expenses. Figure 8 plots probability distribution of OOP expenditures with and without HCME benefits and shows that the right tail of the distribution is thinner with HCME.

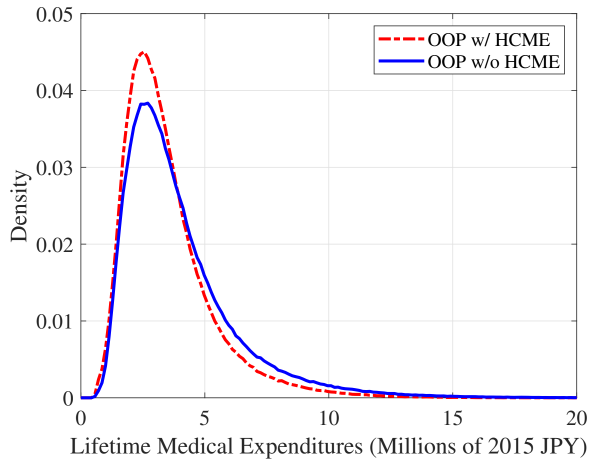


Figure 8: Probability Distribution of Lifetime Medical Expenditures (Men): Out-of-pocket with and without HCME

Note: The horizontal axis indicates simulated lifetime medical expenditures (out-of-pocket with and without HCME) in million JPY.

Table 5 shows moments of the lifetime OOP expenditures for men and women, with moments for gross expenditures for comparison. Distribution of the OOP without HCME has a higher skewness, consistent with the thick right tail in Figure 8.

Table 5: Moments of Lifetime Medical Expenditures: Gross, OOP with HCME (1) and OOP without HCME (2)

	Men			Women		
	Gross	OOP(1)	OOP(2)	Gross	OOP(1)	OOP(2)
Mean	20.5	3.5	4.0	21.4	3.6	3.9
Std. dev.	10.9	1.8	2.3	10.2	1.6	1.9
Coeff. of var.	0.53	0.52	0.58	0.48	0.46	0.50
Skewness	1.49	1.81	1.92	1.43	1.63	1.73

Note: Mean and standard deviation are in million JPY.

Alternative Medical Expenditure Process: Table 6 shows moments of lifetime OOP medical expenditures for men and women under alternative assumptions about persistence of expenditure shocks. Probability distributions are displayed in Figure 9. Qualitatively, the differences across specifications are similar to those for gross medical expenditures examined in Fukai et al. (2022).

Table 6: Moments of Lifetime Out-of-pocket Medical Expenditures Under Alternative Processes

	Men				Women			
	M(2)	M(1)	iid	det.	M(2)	M(1)	iid	det.
Mean	3.49	3.54	3.54	3.99	3.57	3.61	3.61	3.93
Std. dev.	1.83	1.50	0.96	0.83	1.63	1.34	0.85	0.65
Coeff. of var.	0.52	0.42	0.27	0.21	0.46	0.37	0.23	0.17
Skewness	1.81	1.04	0.15	-1.22	1.63	0.96	0.07	-1.81

Note: Mean and standard deviation are in million JPY.

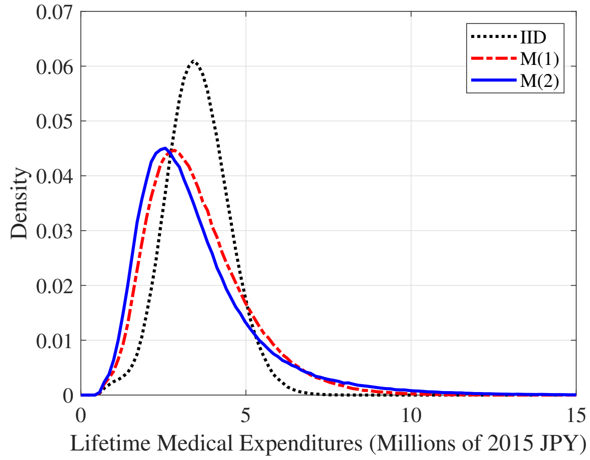


Figure 9: Probability distribution of Lifetime Out-of-pocket Medical Expenditures under Alternative Processes (Men)

Note: The horizontal axis indicates simulated lifetime medical expenditures in million JPY.

High persistence of bad health shocks in the M(2) specification relative to others is reflected in the higher standard deviation and skewness of lifetime OOP expenditures than those under different specifications. There is not much difference in average expenditures across specifications between M(2) and M(1) processes. The small difference, however, at the macro level conceals different experiences across individuals who face persistent bad health shocks.

To demonstrate such differences, we computed lifetime gross and OOP expenditures for individuals who face a bad health shock for the first time in their lives at different ages, followed by another bad health shock in the next period. Average lifetime gross and OOP expenditures are summarized in Table 7.

Table 7: Lifetime Gross and OOP Expenditures and Persistent Bad Health Shocks

Bad at age	30	40	50	60	70	All
Gross M(2)	24.4	25.5	25.7	26.0	26.3	20.5
Gross M(1)	23.0	23.6	25.3	26.0	26.7	20.7
OOP M(2)	4.67	5.04	5.28	4.88	3.32	3.49
OOP M(2)	4.17	4.47	4.74	4.76	3.48	3.53

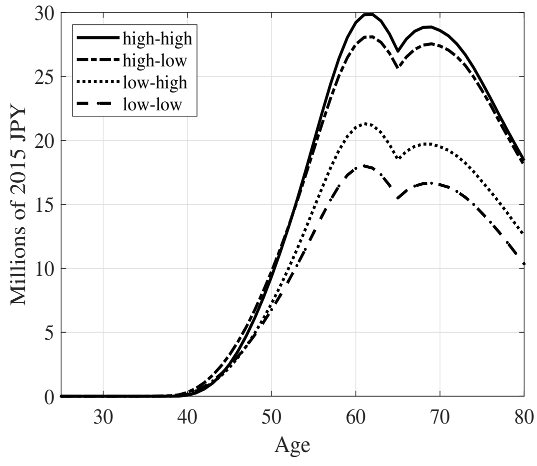
Note: Age denotes the age at which individuals received a bad health shock for the first time, followed by another bad shock in the next period. Expenditures are in million JPY.

As demonstrated in Fukai et al. (2022), for an individual in bad health in the current period at time t, the probability of staying in bad health in the following period at $t+1$ is higher if the individual was already in bad health in the previous period at time $t-1$. This long persistence of health shocks beyond one period is captured in the M(2) process, but not in the M(1). As shown in Table 7, those who receive bad shocks for two periods have higher lifetime expenditures under the M(2) process, at least for those who experienced such shocks for the first time before age 60. Recall also that death probability is positively correlated with expenditures especially at older ages and this is reflected in the reversal of lifetime expenditures between M(1) and M(2) at older ages. Those who receive bad shocks in their 60s or 70s, for example, are more likely to die sooner, which offsets the positive effects of more persistent bad health shocks on lifetime expenditures.

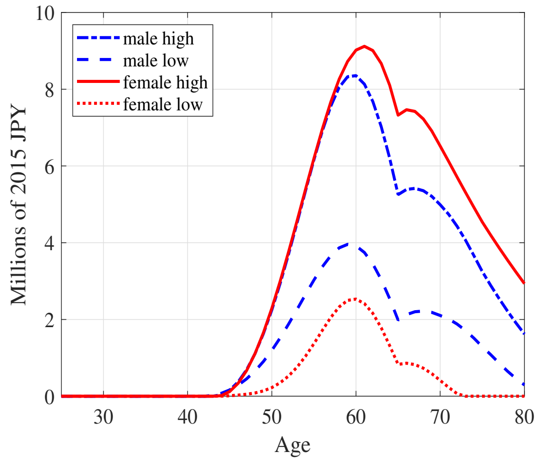
2 More Details on the Structural Model and Quantitative Results

2.1 Savings by Skill Levels in the Baseline Model

In our baseline model, assets differ by skills and health status within a group of the same gender and marital status, as shown in Figure 10. Figure 10a shows asset profiles of married couples by combination of skill levels of men and women, where high-low, for example, indicates a couple comprising a high-skilled husband and a low-skilled wife. Among singles, high-skilled individuals own more than the low-skilled for each gender, as shown in Figure 10b. High-skilled women save more than high-skilled men although their earnings are not very different from their male counterparts on average, since women live longer than men and have stronger life-cycle saving motives. Low-skilled women, however, save much less than low-skilled men as the difference in earnings dominates the difference in longevity.



(a) Married



(b) Singles

Figure 10: Average Assets of Households by Age, Marital Status and Skills

2.2 Roles of the High-cost Medical Expense (HCME) Benefits

High-cost medical expense (HCME) benefits protect individuals from very high medical expenses, with progressive generosity for low income households. Table 8 shows changes in some variables when we assume that the HCME benefits do not exist. Given higher expenditure risks, households increase savings, whether reduced insurance expenditures are paid back as a lump-sum transfer or not. Although the aggregate savings are higher, large medical expenditure shocks will make more individuals be eligible to receive welfare transfers.

Loss of the HCME benefits will lower welfare of both high and low-skilled men and women. With a budget balancing tax transfer of 9,000 yen, although in a relatively small amount, average consumption slightly increases and welfare effects are slightly positive. This is mainly driven by additional consumption of young households with low assets.

Table 8: No High-Cost Medical Expense (HCME) Benefits (Changes from the Baseline Model)

	No tax change	Tax adjusted
Avg. savings	+1.8%	+1.8%
Avg. consumption	-0.3%	+0.2%
Transfer recipients	1.78%	1.73%
	(+5.2%)	(+1.9%)
Lump-sum tax	–	-9,000
Welfare effects		
- All	-0.24%	+0.26%
- Men: low/high	-0.30%/-0.23%	+0.22%/+0.15%
- Women: low/high	-0.20%/-0.20%	+0.36%/+0.21%

2.3 Alternative Specification of Medical Expenditure Risks

This section presents numerical results of the simulations under alternative specification of medical expenditure processes. Table 9 shows changes in average savings, consumption and transfer recipients when we assume the first-order Markov process of medical expenditures, M(1), or a deterministic process. In the latter, we assume that all households face the same age and gender specific expenditures, computed as an average across all individuals of the same age and gender group.

Table 9: Alternative Medical Expenditure Processes

	M(1)	Deterministic
Avg. Savings	+0.18%	+0.87%
Avg. Consumption	-0.02%	-0.33%
Transfer Recipients	1.71%	1.76%
	(+0.8%)	(+3.7%)

Note: The row "Transfer Recipients" indicates the fraction of the population receiving welfare transfers in each experiment. A percentage change in the number of recipients from the baseline model is indicated in parentheses.

2.4 Alternative Parameter Values

In this section we simulate the model under alternative values of preference parameters and quantify their effects on some of our quantitative results.

Discount Factor: In the baseline, we set the value of discount factor β at 0.9586, or approximately 0.96, to match the level of assets at the peak over the life-cycle. We simulate the baseline model where we set the discount factor at 0.95 and 0.97, and compare the effects of extreme scenarios of no insurance with and without taxes. Results are summarized in Table 10. A higher discount factor leads individuals to save more since they place more weight on future consumption. The effects of an extreme scenario of removing health insurance studied in Fukai et al. (2022), with and without tax adjustment, do not differ much under alternative values of β.

Table 10: Extreme Scenarios: No Health Insurance and Full Insurance under Alternative Discount Factors β

	No tax change		
Discount factor β	0.95	0.96	0.97
Change in avg. savings	+39.2%	+38.3%	+38.3%
Change in avg. consumption	-9.7%	-10.0%	-10.2%
Transfer recipients	6.9%	5.8%	4.4%
	(+222.4%)	(+239.7%)	(+256.5%)
Lump-sum tax (JPY)	–	–	–
Welfare effects			
- All	-9.2%	-10.1%	-11.2%
- Men: low/high	-10.1%/-8.2%	-11.1%/-9.1%	-12.3%/-10.2%
- Women: low/high	-9.2%/-8.6%	-9.9%/-9.5%	-11.0%/-10.5%
	Tax adjusted		
Discount factor β	0.95	0.96	0.97
Change in avg. savings	+53.7%	+51.8%	+50.7%
Change in avg. consumption	+2.8%	+3.4%	+4.2%
Transfer recipients	3.6%	2.8%	1.9%
	(+68.9%)	(+64.1%)	(+54.4%)
Lump-sum tax (JPY)	-227,000	-290,000	-309,000
Welfare effects			
- All	+5.0%	+4.8%	+4.7%
- Men: low/high	+5.0%/+3.4%	+4.8%/+3.1%	+4.7%/+2.8%
- Women: low/high	+6.2%/+3.8%	+6.1%/+3.5%	+6.1%/+3.3%

Note: The middle column is for the baseline, where β is approximately 0.96 (0.9586). The row "Transfer Recipients" indicates the fraction of the population receiving welfare transfers in each experiment. The percentage change in the number of recipients from the baseline model is indicated in parentheses. Lump-sum tax is expressed as an annual tax collected in Japanese yen. A negative number indicates a positive transfer from the government to each individual.

Risk Aversion: Table 11 shows effects of no insurance under different values of risk aversion parameter σ. As shown in the top panel of the table for the case of no tax change, loss of insurance induces more savings in a model with a higher σ and welfare effects are more negative. Since individuals save more to insure themselves against expenditure risks, fewer individuals would be eligible for means-tested transfers. Government expenditures for welfare transfers would be lower with higher risk aversion, and when taxes are adjusted, a larger lump-sum transfer is given to individuals.

Table 11: Extreme Scenarios: No Health Insurance and Full Insurance under Alternative Risk Aversion Parameter σ

	No tax change		
Risk Aversion Parameter σ	2	3	4
Change in avg. savings	+16.0%	+38.3%	+48.4%
Change in avg. consumption	-9.1%	-10.0%	-10.5%
Transfer recipients	9.4%	5.8%	3.7%
	(+251.0%)	(+239.7%)	(+255.2%)
Lump-sum tax (JPY)	–	–	–
Welfare effects			
- All	-4.4%	-10.1%	-16.5%
- Men: low/high	-4.7%/-4.0%	-11.1%/-9.1%	-18.4%/-15.1%
- Women: low/high	-4.5%/-4.2%	-9.9%/-9.5%	-15.7%/-15.7%
	Tax adjusted		
Risk Aversion Parameter σ	2	3	4
Change in avg. savings	+33.6%	+51.8%	+60.9%
Change in avg. consumption	+1.7%	+3.4%	+4.6%
Transfer recipients	5.7%	2.8%	1.5%
	(+111.3%)	(+64.1%)	(+44.2%)
Lump-sum tax (JPY)	-244,000	-290,000	-321,000
Welfare effects			
- All	+1.6%	+4.8%	+8.5%
- Men: low/high	+1.8%/+1.0%	+4.8%/+3.1%	+7.9%/+5.0%
- Women: low/high	+2.2%/+1.1%	+6.1%/+3.5%	+10.7%/+6.0%

Note: The row "Transfer Recipients" indicates the fraction of the population receiving welfare transfers in each experiment. The percentage change in the number of recipients from the baseline model is indicated in parentheses. Lump-sum tax is expressed as an annual tax collected in Japanese yen. A negative number indicates a positive transfer from the government to each individual.

3 More Details of Calibration

3.1 Frailty Index

In this section we explain how we calibrated the frailty index used to introduce correlation between health status and earnings in Fukai et al. (2022).

Data Description: We use the Japanese Study of Aging and Retirement (JSTAR) to study the correlation between health and labor force participation. JSTAR is a panel survey of elderly people aged 50 and over, conducted by the Research Institute of Economy, Trade and Industry (RIETI), Hitotsubashi University and The University of Tokyo. The survey has been conducted every two years since 2007. The survey is designed to ensure maximum comparability with preceding surveys such as the Health and Retirement Study (HRS). Although the survey includes some questions about medical expenditures, we found that they are not comparable to those of the NDB. Therefore, we instead computed an objective measure of health status: "the frailty index" from JSTAR, following the method of Hosseini et al. (2021). Hosseini et al. (2021) obtained the frailty index using not only PSID but also HRS, and we can calculate a frailty index using a similar construction method. We use the data between 2007 and 2013.[4]

Construction of Frailty Index: Following the strategy taken in Hosseini et al. (2021), we use 37 variables that take a value between 0 and 1 and calculate the frailty index by summing up all variables with equal weight and then normalizing them to a value between 0 and 1. These variables mainly consist of activities of daily living (ADL)/Instrumental ADL (IADL) variables, past and present disease-related variables, cognitive variables, and health care utilization (outpatient visits, etc.).

- <u>ADL/IADL variables (Difficulties in following activities):</u> Eating using tableware by yourself; putting on and taking off stockings, socks and shoes; getting into and out of bed; using the toilet; bathing by yourself; walking around the room; walking 100 meters; making a phone call without help; managing money;[5] shopping for daily necessities; boiling water in a kettle; getting up from a chair after sitting continuously for a long time; squatting or kneeling; lifting or carrying an object weighing 5kg or more; taking medicine without help; taking one step up the stairs without using the handrail; picking up a small object such as a one-yen coin from a desktop with your fingers; raising your arms above your shoulder; pushing or pulling a large object such as a chair or sofa; going out using public transformation.

- <u>Past and present disease variables (ever had any of the following conditions):</u> High blood pressure; diabetes; cancer or other malignant tumor (including leukemia, lymphoma; excluding benign skin cancer); chronic lung disease (chronic bronchitis, emphysema, etc.; excluding lung cancer); heart disease (angina, heart failure, cardiac infarction, heart valve disease, etc); stroke; joint disorder; asthma; other serious, chronic conditions (liver disease, parkinson's, etc.); BMI ≥ 30; has ever smoked.

[4]For our research purpose, we don't use the data of seven cities from the 2011 survey because there are not enough variables to calculate the frailty index. The seven cities are: Adachi, Kanazawa, Shirakawa, Sendai, Takikawa, Tosu and Naha.

[5]This variable is calculated using the following three questions: paying bills, making deposits in and withdrawals from your bank or postal account, and filling out documentation such as pension forms. We sum these three variables and normalize them to a value between 0 and 1, with 1 meaning that individuals can't do these activities.

- Cognitive variables (ever had any of the following conditions): Dementia; depression or emotional disorder.

- Health care utilization: Outpatient visit; inpatient visit; formal home care utilization; institutional long-term care utilization.

Using the frailty index, we define health status by dividing it into four categories using ten-year age groups. Then, we compute the correlation between health status and labor force participation by gender and age, and estimate the health-dependent labor force participation by gender, age, skill, and marital status. Since the JSTAR does not cover individuals below age 50, we extrapolate our estimates for younger age groups by using Hosseini et al. (2020)'s estimation results from the PSID and assuming that non-participation rates by health status will decline at the same speed as Hosseini et al. (2020).

3.2 Long-Term Care Expenditures

As discussed in the calibration section of Fukai et al. (2022), long-term care expenditures cover expenditures for individuals aged 40 and above. We report below expenditure data obtained from the Statistics of Long-term Care Benefit Expenditures of the Ministry of Health, Labour and Welfare (MHLW).[6] They report total expenditures for different types of long-term care services by gender and age groups. We combine these and demographic data, and compute average long-term care expenditures by age and gender. Figure 11 shows the life-cycle profile of gross long-term care expenditures.

[6]https://www.mhlw.go.jp/toukei/list/45-1.html (Japanese)
https://www.mhlw.go.jp/english/database/db-hss/soltcbe.html (English)

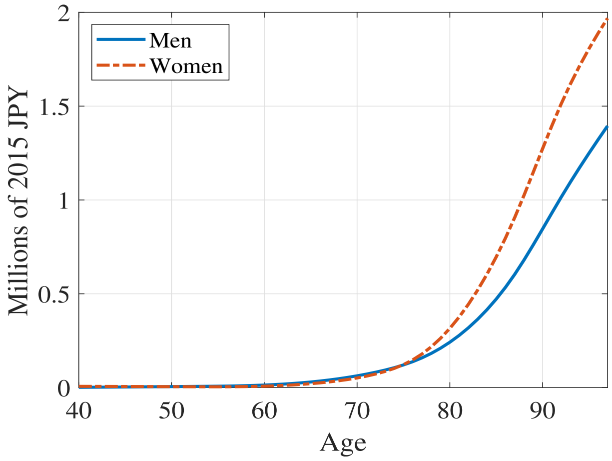


Figure 11: Annual Long-term Care Expenditures by Age and Gender

Note: Figure shows the average gross long-term care expenditures of all individuals by age and gender in 2015. Expenditure data is constructed from monthly data from January 2015 to December 2015, converted to annual data. The expenditure data is from the Statistics of Long-term Care Benefit Expenditures of the Ministry of Health, Labor and Welfare (MHLW). The population data is from the Population Statistics of the National Institute of Population and Social Security Research (IPSS).

References

Fukai, T., H. Ichimura, S. Kitao, and M. Mikoshiba (2022). Medical expenditures over the life-cycle: Persistent risks and insurance. Working Paper.

Hosseini, R., K. Kopecky, and K. Zhao (2020). How important is health inequality for lifetime earnings inequality? Working Paper.

Hosseini, R., K. Kopecky, and K. Zhao (2021). The evolution of health over the life cycle. Working Paper.