Modelling mortality heterogeneity in longevity risk applications using health trajectories and multimorbidity

Michelle Vhudzijena[1,2], Michael Sherris[1,2], Andrés Villegas[1,2] and Jonathan Ziveyi[1,2]

[1]ARC Centre of Excellence in Population Ageing Research
[2]School of Risk and Actuarial Studies
University of New South Wales, Sydney, Australia

Outline

- Introduction
- Data
- Methodology
- Results
- Conclusion

Background

- Demand for long–term care is expected to increase globally in the next few years as more than 50% of individuals aged 65 and above are expected to need long–term care
- Public spending on long term care ranges between 0.5% to 4% of Gross Domestic Product (GDP) in OECD countries
- Private markets offer long–term care insurance products in the form of traditional insurance policies or hybrid products that combine life insurance/annuities with long–term care

Literature review

Ageing Population

Definitions

Presence of 2 or more diseases with or without impairment (Marengoni et al. 2012)

Indexation approach (Charlson et al. 1987, Greenfield et al. 1983, Imamura et al. 1997)

Pool of diseases, Fortin et al. 2012 recommend considering 12 or more diseases to reduce variability in prevalence estimates

Prevalence

Kingston et al. (2018) estimate that more than half of the older population will have multimorbidity from 2015-2035.

Risk factors

Being older, female and having a lower socio-economic status are associated with multimorbidity (Van den Akker et al. 1998, 2000)

Literature gaps

Sherris and Wei (2021) propose a five state health status and disability model but do not consider multimorbidity

Three state models of health and functional disability do not distinguish between multimorbid and healthy individuals (Fong, Shao and Sherris, 2015; Li, Shao and Sherris, 2017; Fu, Sherris and Xu, 2021)

Multi–state models are used to calculate mortality rates, incidence and prevalence rates of multimorbidity for both men and women (Kingston et al. 2018; Chan et al. 2019). However, *they do not consider functional disability or recovery from multimorbidity*

No link in the literature between multimorbidity and the pricing of long term care products

How do we incorporate multimorbidity in actuarial pricing?

Why should we care?

- “Two issues make the decumulation problem tricky. Most people have spent all of their lives living on a paycheck, so they have no experience taking a pot of money and turning it into income. So it seems sensible that annuities would be part of the income equation. But annuities are challenging: Employees shun them, and when they do use them, they use the wrong ones, at least from the point of view of most economists” Richard Thaler, Nobel Prize Winner 2017
- Actuaries role in designing and pricing fair and sustainable decumulation products

Relationship to Sustainable Development Goals

Research questions

1. What is the impact of multimorbidity on transition rates in a 3–state model of health status and functional disability?
2. To what extent does a five state model of multimorbidity and functional disability capture differences in mortality and functional disability risks?
3. What are the pricing implications for the incorporation of multimorbidity in long term care insurance, life annuities and life-care annuities?

Health Retirement Study

- We use data from the University of Michigan Health Retirement Study (HRS) which follows Americans aged 50 and above
- Multi–state models are fit using ADLs from wave 4 to 13 similar to previous studies using this dataset (Fong, Shao, and Sherris 2015; Li, Shao, and Sherris 2017; Shao, Sherris, and Fong 2017; Sherris and Wei 2020; Hanewald, Shao, and Li 2019; Wang, Hanewald, and Wang 2022).
- We exclude individuals who provide inappropriate responses, who fail to respond in any wave and those who do not appear in consecutive interview dates.
- We define multimorbidity as the presence of more than one chronic conditions from the following doctor diagnosed conditions: high blood pressure, diabetes, cancer, lung disease, heart problems, stroke, psychiatric problems, and arthritis

Definitions

Activities of daily living

Functional disability is triggered when an individual has some difficulty in 2 or more activities of daily living

Note. Reprinted from "User Experience Design of Stroke Patient Communications Using Mobile Finger (MOFI) Communication Board With User Center Design Approach", by Priana et al. , 2018, *International Journal of Interactive Mobile Technologies*,12

Functional disability model

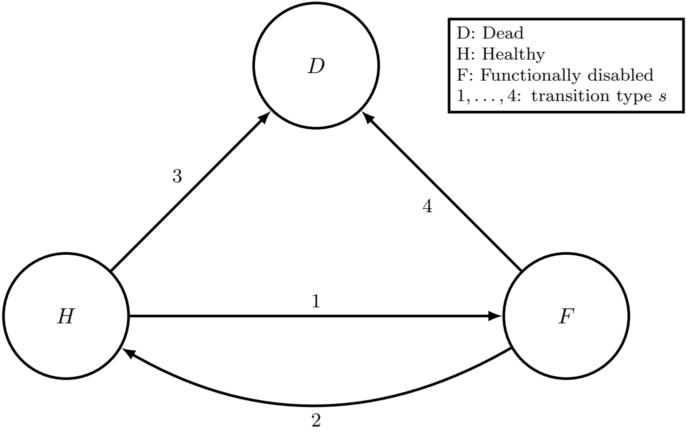


Figure 1: Three state functional disability model

Five state model of multimorbidity and functional disability

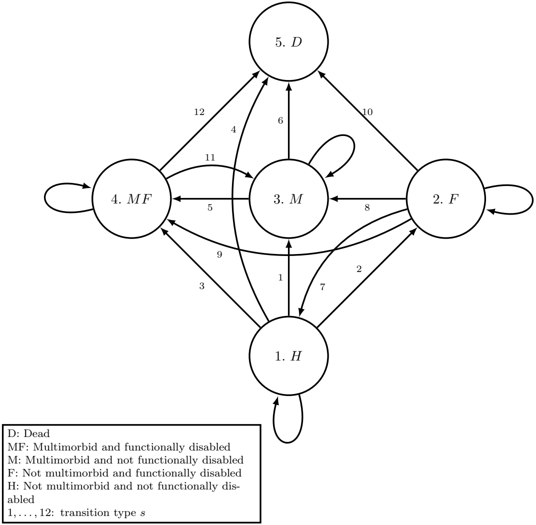


Figure 2: Five–state multimorbidity and functional disability model

Extending three state models

Following the proportional hazard specification in Li, Shao, and Sherris (2017); Sherris and Wei (2020), we model the transition intensity of type $s = 1, \ldots, S$ for an individual k for $k = 1, \ldots, K$ at time t years with

$$\lambda_{k,s}(t) = \exp(\beta_s + \gamma_s' w_k(t) + \alpha_s \psi(t)) H_{k,s}(t),$$

where β_s is the time invariant baseline log–intensity for transition type s, $w_k(t)$ is a vector of the observed predictors for each individual k, $\psi(t)$ is frailty which is a stochastic latent process, γ_s is a vector measuring the sensitivity of $\lambda_{k,s}(t)$ with respect to $w_k(t)$, α_s is a scalar measuring the sensitivity of $\lambda_{k,s}(t)$ with respect to $\psi(t)$ and $H_{k,s}(t) = 1$.

Multi–state models I

Static model

The transition rate $\lambda_{k,s}(t)$ is assumed to be dependent on age and sex only:

$$\ln \lambda_{k,s} = \beta_s + \gamma_s^{age} x_k(t) + \gamma_s^{female} F_k + \gamma_s^{multimorbidity} M_k \quad (1)$$

where $x_k(t)$ is the k^{th} individual's age at time t, F_k is the binary variable indicating the gender for the individual k, M_k is the categorical variable indicating the multimorbidity of an individual k, γ_s^{age} measures the sensitivity of $\ln \lambda_{k,s}(t)$ with respect to age, γ_s^{female} measures the sensitivity of $\ln \lambda_{k,s}(t)$ with respect to gender and $\gamma_s^{multimorbidity}$ measures the sensitivity of $\ln \lambda_{k,s}(t)$

Multi–state models II

Model with systematic trend

$$\ln \lambda_{k,s} = \beta_s + \gamma_s^{age} x_k(t) + \gamma_s^{female} F_k + \phi_s^{time} t + \gamma_s^{multimorbidity} M_k \quad (2)$$

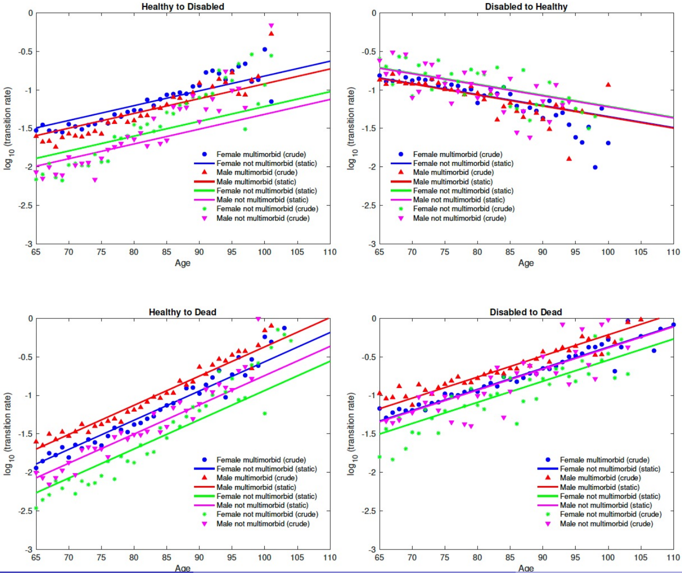
where ϕ_s measures the sensitivity of $\ln \lambda_{k,s}(t)$ with respect to the time trend t.

Frailty model with systematic trend and uncertainty

$$\ln \lambda_{k,s} = \beta_s + \gamma_s^{age} x_k(t) + \gamma_s^{female} F_k + \phi_s^{time} t + \alpha_s \psi_i + \gamma_s^{multimorbidity} M_k \quad (3)$$

where α_s measures the sensitivity of $\ln \lambda_{k,s}(t)$ with respect to the latent factor ψ that is modelled as a random walk

Exploratory model



Functional disability model I

Table 1: Three state static model with multimorbidity: estimated parameters with standard errors in parentheses

Transition	H→F		F→H		H→D		F→D	
s	1		2		3		4	
$\hat{\beta}_s$	-4.5836	***	-1.6566	***	-4.7699	***	-3.0919	***
	(0.0276)		(0.0394)		(0.0307)		(0.0564)	
$\hat{\gamma}_s^{\text{age}}$	0.4431	***	-0.3302	***	0.8740	***	0.6315	***
	(0.0105)		(0.0121)		(0.0119)		(0.0139)	
$\hat{\gamma}_s^{\text{female}}$	0.2326	***	0.0192		-0.4462	***	-0.3672	***
	(0.0224)		(0.0310)		(0.0233)		(0.0302)	
$\hat{\gamma}_s^{\text{multimorbidity}}$	0.9124	***	-0.3064	***	0.8601	***	0.3900	***
	(0.0270)		(0.0381)		(0.0299)		(0.0506)	
Log likelihood	-95674							

† *Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$;

†† Age covariate is calculated using age last birthday.

Functional disability model II

Table 2: Three state trend model with multimorbidity: estimated parameters with standard errors in parentheses

Transition	H→F		F→H		H→D		F→D	
s	1		2		3		4	
$\hat{\beta}_s$	-4.4453	***	-1.4445	***	-4.6476	***	-2.9798	***
	(0.0321)		(0.0449)		(0.0353)		(0.0605)	
$\hat{\gamma}_s^{\text{age}}$	0.4448	***	-0.3345	***	0.8770	***	0.6320	***
	(0.0105)		(0.0121)		(0.0120)		(0.0140)	
$\hat{\gamma}_s^{\text{female}}$	0.2331	***	0.0103		-0.4469	***	-0.3729	***
	(0.0224)		(0.0311)		(0.0233)		(0.0302)	
$\hat{\gamma}_s^{\text{multimorbidity}}$	0.9357	***	-0.2609	***	0.8827	***	0.4148	***
	(0.0271)		(0.0384)		(0.0300)		(0.0509)	
$\hat{\gamma}_s^{\text{time}}$	-0.1710	***	-0.2596	***	-0.1536	***	-0.1385	***
	(0.0207)		(0.0275)		(0.0224)		(0.0276)	
Log likelihood	-95559							

† *Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$;

†† Age covariate is calculated using age last birthday.

Five state parameter interpretation I

- Mortality rates increase with age *(H→D, M→D, F→D and MF→D)*
- Disability rates increase with age *(H→F, H→MF and M→MF)*
- Multimorbidity rates from the healthy state increase with age *(H→M, H→MF)*
- Multimorbidity from the functionally disabled state decreases with age *(F→MF)*
- Recovery rates from functional disability decrease with age *(F→H, F→M and MF→M)*

Five state parameter interpretation II

Females have lower mortality rates and more likely to become disabled than males

Females are more likely to become multimorbid and functionally disabled than males

(H→MF and M→MF)

Females are less likely to become multimorbid than males

(H→M, H→MF)

Five state multiyear transition probabilities I

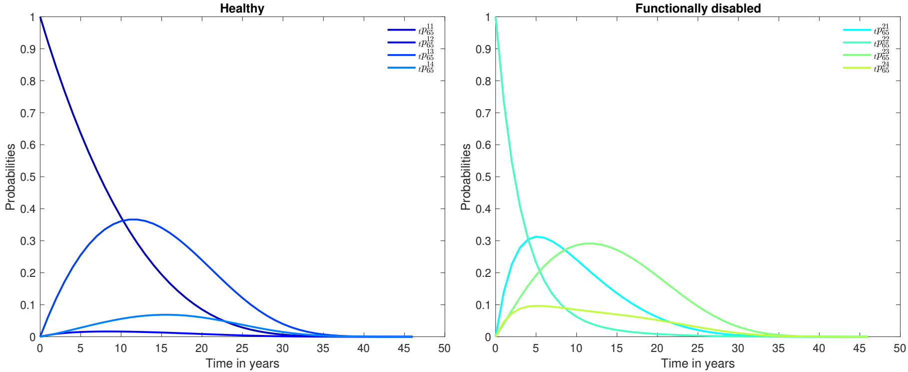


Figure 3: Multiyear transition probabilities for males aged 65 using static model

Five state multiyear transition probabilities II

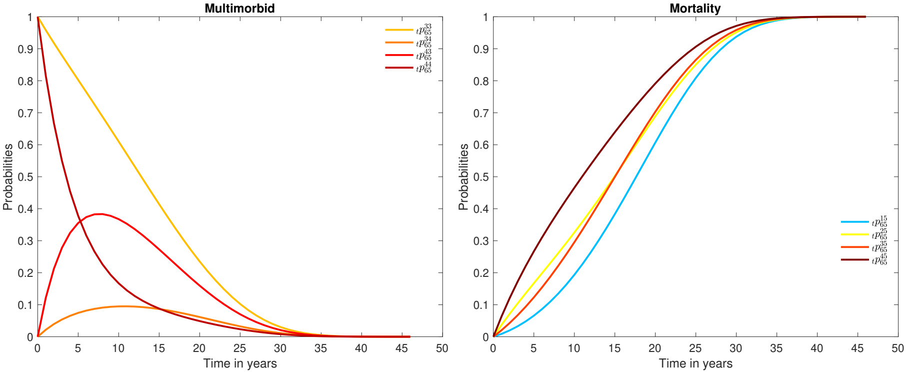


Figure 4: Multiyear transition probabilities for males aged 65 using static model

Three state functional disability model

Table 3: Future lifetime statistics for 65–year old healthy individuals using static models

	Overall		Multimorbid		Not multimorbid	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**
Life expectancy	19.4374	16.7356	17.7624	14.9566	25.4529	22.1659
Healthy life expectancy	16.4161	14.9753	14.4357	12.9698	23.0100	20.7304
Disabled life expectancy	3.0213	1.7603	3.3267	1.9868	2.4429	1.4355
Healthy life expectancy over life expectancy	0.8532	0.9006	0.8269	0.8793	0.9043	0.9344
Age at onset of disability conditional on becoming disabled	79.0227	78.0685	77.1294	76.2282	83.7364	82.0354

Findings

- The 5 state model shows the differences in life expectancy based on both multimorbidity and functional disability and captures the dynamics of how multimorbidity and functional disability evolve over time
- Using a predictor for multimorbidity as shown in the 3 state model tends to overestimate life and healthy expectancy which has significant impact on the pricing of annuities and other longevity linked products
- Consequently, HLE/TLE is overestimated in the 3 state model
- Individuals spend more time multimorbid than disabled

Premiums of longevity linked products

Table 4: Comparison of premiums for insurance products using three state model and five state model for males and females

	Males		Females	
State	**Static**	**Trend**	**Static**	**Trend**
Difference from healthy state for life annuity				
Healthy	15.18%	16.73%	12.63%	13.75%
Multimorbid and not functionally disabled	1.74%	1.95%	0.74%	0.92%
Difference from healthy state for long term care				
Healthy	2.29%	3.54%	1.82%	3.27%
Multimorbid and not functionally disabled	28.80%	29.25%	31.19%	31.68%
Difference from healthy state for life care annuity				
Healthy	14.76%	16.29%	12.68%	13.97%
Multimorbid and not functionally disabled	10.11%	10.63%	12.63%	13.31%

[a] All premiums compared to healthy state in three state model

Contributions

- We extend the literature on multiple state health modelling by comparing 2 methods of integrating multimorbidity in multiple state modelling
- We develop a 5 state model of multimorbidity and functional disability with recovery that captures differences in disability onset, morbidity onset, healthy life expectancy and future life expectancy
- We extend the 3 state health and functional disability models by quantifying the impact of multimorbidity on transition rates
- We demonstrate the effects of these differences in the pricing of various longevity and health–linked products for morbid and non–morbid groups

Weaknesses

Limitations

- Small sample size

Future work

- Pricing for long term care and annuities
- Comparison of future lifetime statistics

Acknowledgements

- This research is supported by the Australian Research Council Centre of Excellence in Population Ageing Research (project number CE170100005)
- This research includes computations using the computational cluster Katana supported by Research Technology Services at UNSW Sydney.

References I

Fong, Joelle H, Adam W Shao, and Michael Sherris. 2015. "Multistate Actuarial Models of Functional Disability." *North American Actuarial Journal* 19 (1): 41–59. https://doi.org/10.1080/10920277.2014.978025.

Fu, Yu, Michael Sherris, and Mengyi Xu. 2021. "Functional disability with systematic trends and uncertainty: a comparison between China and the US." *Annals of Actuarial Science*, 1–30. https://doi.org/10.1017/S1748499521000233.

Hanewald, Katja, Adam W Shao, and Han Li. 2019. "Modelling multi-state health transitions in China: A generalised linear model with time trends." *Annals of Actuarial Science* 13 (1): 145–65. https://doi.org/10.1017/S1748499518000167.

References II

Li, Zixi, Adam W Shao, and Michael Sherris. 2017. "The Impact of Systematic Trend and Uncertainty on Mortality and Disability in a Multistate Latent Factor Model for Transition Rates." *North American Actuarial Journal* 21 (4): 594–610. https://doi.org/10.1080/10920277.2017.1330157.

Shao, Adam W, Michael Sherris, and Joelle H Fong. 2017. "Product pricing and solvency capital requirements for long-term care insurance." *Scandinavian Actuarial Journal* 2017 (2): 175–208. https://doi.org/10.1080/03461238.2015.1095793.

Sherris, Michael, and Pengyu Wei. 2020. "A Multi-state Model of Functional Disability and Health Status in the Presence of Systematic Trend and Uncertainty." *North American Actuarial Journal*, February, 1–23. https://doi.org/10.1080/10920277.2019.1708755.

References III

Wang, Qiqi, Katja Hanewald, and Xiaojun Wang. 2022. "Multistate health transition modeling using neural networks." *Journal of Risk and Insurance* 89 (2): 475–504. https://doi.org/10.1111/JORI.12364.