Modeling multi-state health transitions in China: A generalized linear model with time trends

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Australia-China Population Ageing Research Hub

- Website: **http://www.cepar.edu.au/research/australia-china-population-ageing-research-hub**
- Based in the ARC Centre of Excellence in Population Ageing Research (CEPAR) at UNSW Sydney; funded by UNSW Sydney
- Research areas focusing on China:
  1. Aging trends
  2. Long-term care services and insurance
  3. Mature labor force participation
  4. Retirement incomes, financial products and housing
- Team:
  - Director: Prof John Piggott
  - Scientific Director: Prof Hanming Fang (University of Pennsylvania)
  - 4 full-time research fellows, 3 PhD students

Motivation

- Rapid population aging in China
- In 2015, **1** in **5** older persons (aged 65+) **globally** lived in China, while in 2050, **1** in **4** elderly (over 370 million people) will be Chinese (United Nations, 2015).
- China's old age dependency ratio was 15% in 2015, will be close to 50% by mid-century (United Nations, 2015)
- Need for retirement planning, long-term care, and financial services for the elderly in China

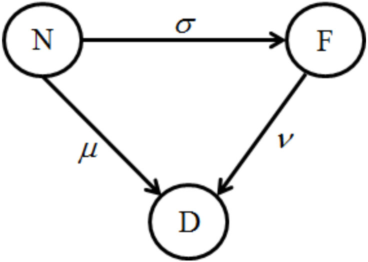
Motivation

- Traditional family-based care under threat
  - Demographic changes, weakening of traditional values, greater geographic mobility, improved gender equality (see, e.g., Zhu, 2015; Lu *et al.*, 2015).
- Current social security programs do not cover full nursing home cost; do not fund community-based services (Yang *et al.*, 2013)
- Need for social security programs and/or private market solutions (e.g. LTC insurance, specialized home equity release products)
- **Need to understand and model health transitions among Chinese elderly**

Our paper

- We develop a generalized linear model (GLM) to estimate health transition intensities in a three-state Markov model
  - Builds on previous models developed by Renshaw and Haberman (1995) for UK data and Fong *et al.* (2015) for US data
  - Our model includes age effects, time trends and age-time interactions
- Provide first evidence on health transitions of Chinese elderly

Three-state time-inhomogeneous Markov process



- State N: non-disabled
- State F: functionally disabled
- State D: dead (absorbing)

Existing models for functional disability

- Renshaw and Haberman (1995):

$$\log(\sigma_x) = \beta_0 + \beta_1 x + \beta_2 x^2 \quad (1)$$

$$\log(\varphi_{x,z}) = \beta_0 + \beta_1 x + \beta_2 z + \beta_3 \sqrt{z} + \beta_4 xz + \beta_5 x\sqrt{z} \quad (2)$$

$$\log(\nu_{x,z}) = \beta_0 + \beta_1 x + \beta_2 z + \beta_3 (z - z_1)_+ + \beta_4 (z - z_2)_+ \quad (3)$$

  Data: UK Male permanent health insurance data during 1975–1978.

- Fong *et al.* (2015):

$$\eta_x = \sum_{s=0}^{k} \beta_s x^s \quad (4)$$

  where $\eta_x = \log(\mu_x),\ \log(\sigma_x), \log(\varphi_x)$, or $\log(\nu_x)$.

  Data: Health and retirement Study (HRS), 1998–2010.

- Li *et al.* (2017):

$$\ln(\lambda_{skx}(t)) = \beta_s + \gamma_s^{female} x_t + \gamma_x^{female} F + \phi_s t + \alpha_s \varphi(t) \quad (5)$$

  where t is the linear trend and $\varphi(t)$ is the latent factor or frailty.

  Data: Health and retirement Study (HRS), 1998–2010.

Stochastic mortality models

- Lee and Carter (1992):

$$\log(m_{x,t}) = a_x + b_x \kappa_t, \tag{6}$$

where a_x and b_x represent age effects and κ_t represents time effect.

- Cairns *et al.* (2006):

$$\text{logit}(q_{x,t}) = \kappa_t^1 + \kappa_t^2 (x - \bar{x}), \tag{7}$$

where κ_t^1 and κ_t^2 are time effects and are assumed to follow a bivariate random walk with drift process.

- Renshaw and Haberman (1996):

$$\log(\mu_{x,t}) = \beta_0 + \sum_{j=1}^{s} \beta_j L_j(x') + \sum_{i=1}^{r} \alpha_i t'^i + \sum_{i=1}^{r} \sum_{j=1}^{s} \gamma_{ij} L_j(x') t'^i, \tag{8}$$

where L_j is the j^{th} Legendre orthogonal polynomial.

A Generalized Linear Model

Link function: Adopt a log link function $g(\cdot)$:

$$g(\alpha_{x,t}) = \ln(\alpha_{x,t}) = \eta_{x,t}, \tag{9}$$

for $\eta_{x,t} = \log(\mu_{x,t})$, $\log(\sigma_{x,t})$ or $\log(\nu_{x,t})$.

Linear predictor: Introduce a time trend and age-time interactions:

$$\boldsymbol{\eta_{x,t} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 t + \beta_4 tx + \beta_5 tx^2} \tag{10}$$

Probability distribution: Assume that the number of health transitions follows an independently distributed Poisson distribution.

Estimation and model selection: MLE, compare all possible model variants using BIC.

Our contribution

- We **combine** good model features and estimation techniques from multi-state models and mortality models.
- We **allow** for greater flexibility in the model and explore different functional forms.
- We **incorporate** a time trend in the transition intensities.
- We **compare** the distinct demographic differences between males and females in urban and rural areas in China.

Chinese Longitudinal Healthy Longevity Survey (CLHLS)

- Conducted by the Center for Healthy Aging and Family Studies (CHAFS) at the National School of Development at Peking University
- 22 of China's 31 provincial regions
- 6 waves: 1998, 2000, 2002, 2005, 2008, 2011
- Largest longitudinal survey of the "oldest old"(aged 80+) internationally
- Information on health status and quality of life of the elderly

Our sample

- Unbalanced panel, all individuals with 2+ consecutive observations
- Health transitions between 2 waves: 5 pairwise observations
- Focus on older ages 65–105
- Separate data for males/females and urban/rural
- We define the state “F” as having difficulties to perform 2+ **Activities of Daily Living (ADL)**: bathing, dressing, eating, toileting, continence and transferring in and out of bed.

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Sample size

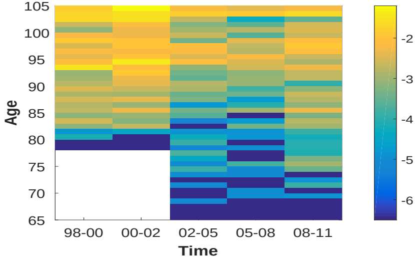
Table: Number of transition counts.

Time	σ: N $\rightarrow$ F				μ: N $\rightarrow$ D				ν: F $\rightarrow$ D			
	Males		Females		Males		Females		Males		Females	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
1998 - 00	99	153	175	292	277	604	362	793	141	240	284	649
2000 - 02	191	131	376	256	572	416	642	520	202	143	498	350
2002 - 05	168	134	257	278	720	1,020	860	1,333	248	275	608	728
2005 - 08	105	109	193	207	686	1,013	824	1,324	196	180	463	537
2008 - 11	214	229	306	443	620	1,229	757	1,682	145	192	368	642
Total	777	756	1,307	1,476	2,875	4,282	3,445	5,652	932	1,030	2,221	2,906

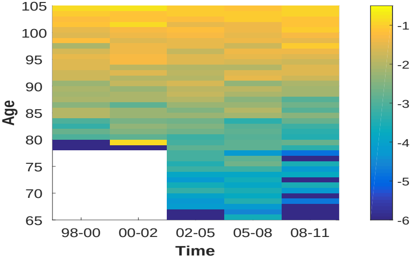
Table: Number of exposure years.

Time	State N				State F				Total
	Males		Females		Males		Females		
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	
1998 - 2000	1,763	2937	2,189	3,971	369	519	797	1,537	14,082
2000 - 2002	3,240	1,997	3,652	2,568	571	347	1,258	819	14,451
2002 - 2005	5,570	7,516	6,474	8,801	793	742	1,661	1,926	33,482
2005 - 2008	5,215	7,552	5,917	9,182	614	544	1,385	1,573	31,980
2008 - 2011	4,946	8,627	5,609	10,249	662	762	1,379	1,979	34,211
Total	20,733	28,628	23,840	34,770	3,008	2,914	6,480	7,834	128,206

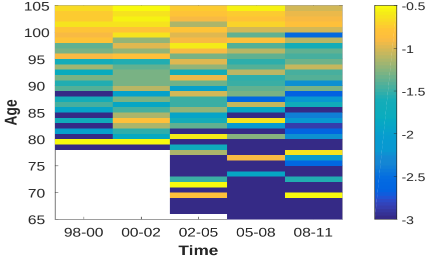
Plots of crude transition rates: urban females



(a) σ: N $\rightarrow$ F



(b) μ: N $\rightarrow$ D



(c) ν: F $\rightarrow$ D

Optimal model: parameter estimates

Coeffiecient	σ: N $\to$ F Males Urban	σ: N $\to$ F Males Rural	σ: N $\to$ F Females Urban	σ: N $\to$ F Females Rural	μ: N $\to$ D Males Urban	μ: N $\to$ D Males Rural	μ: N $\to$ D Females Urban	μ: N $\to$ D Females Rural
β_0	-5.376***	-5.719***	-6.346***	-5.969***	-4.237***	-4.292***	-4.684***	-4.414***
β_1	0.122***	0.127***	0.217***	0.169***	0.119***	0.140***	0.137***	0.123***
$\beta_2(\times 10^2)$	-0.111***	-0.09**	-0.259***	-0.178***	-0.808***	-0.132***	-0.110***	-0.090***
β_3								
$\beta_4(\times 10^2)$			-0.154***	-0.158***				
$\beta_5(\times 10^5)$		-5.125***						
BIC	832.77	824.56	977.70	1107.56	943.25	1071.52	940.41	1023.65

Coeffiecient	ν: F $\to$ D Males Urban	ν: F $\to$ D Males Rural	ν: F $\to$ D Females Urban	ν: F $\to$ D Females Rural
β_0	-2.267***	-2.186***	-2.619***	-2.618***
β_1	0.046***	0.047***	0.053***	0.053***
$\beta_2(\times 10^2)$				
β_3	-0.027***	-0.029***	-0.026***	
$\beta_4(\times 10^2)$				
$\beta_5(\times 10^5)$				-1.622***
BIC	691.81	715.48	754.76	746.89

Note: Linear predictor: $\eta_{x,t} = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 t + \beta_4 tx + \beta_5 tx^2$.
$^{*}p < 0.05;^{**}p < 0.01$.

Estimation results

Example: urban females

- $\log(\sigma_x) = -6.346 + 0.217x - 0.00259x^2 - 0.00154tx$ (disability rate)
- $\log(\mu_x) = -4.684 + 0.137x - 0.00110x^2$ (mortality rate from “N”)
- $\log(\nu_{x,t}) = -2.619 + 0.053x - 0.026t$ (mortality rate from “F”)

Life expectancy and healthy life expectancy

- Use optimal models to compute LEs at age 65 and 75 conditional on initial health status and HLEs
- Results agree with Liu *et al.* (2009); Luo *et al.* (2016); Guo (2017)

Table: Healthy life expectancy at age 65 and 75.

Year	Male Urban	Male Rural	Female Urban	Female Rural
	Healthy life expectancy at 65			
1998	15.16	15.03	16.85	16.26
2011	15.16	15.17	17.36	16.68
2020	15.16	15.25	17.66	16.93
	Healthy life expectancy at 75			
1998	8.96	8.58	9.64	9.56
2011	8.96	8.76	10.21	10.04
2020	8.96	8.86	10.54	10.31

Conclusion

- **Summary:** A new flexible approach to modeling health transitions at higher ages based on the GLM framework.
  - Model allows for time trends and age-time interactions
  - Results for Chinese aged 65-105 (males/females, urban/rural)
- **Results:**
  - Time trends and age-time interactions are important for modeling disability rates and disabled mortality rates
  - Estimated LEs and HLEs: persistent rural/urban health inequalities
- **Potential applications of the model:**
  - Estimate the demand for LTC services and insurance
  - Analyze other health conditions (chronic diseases, critical illnesses)

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Thank you!

Any questions, comments or suggestions?

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