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Abstract

China and the U.S. are two contrasting countries in terms of functional disability and long-term care. China is experiencing declining family support for long-term care and developing private long-term care insurance. The U.S. has a more developed public aged care system and private long-term care insurance market than China. Changes in the demand for long-term care are driven by the levels, trends and uncertainty in mortality and functional disability. To understand the future potential demand for long-term care, we compare mortality and functional disability experiences in China and the U.S., using a multi-state latent factor intensity model with time trends and systematic uncertainty in transition rates. We estimate the model with the Chinese Longitudinal Healthy Longevity Survey (CLHLS) and the U.S. Health and Retirement Study (HRS) data. The estimation results show that if trends continue, both countries will experience longevity improvement with morbidity compression and a declining proportion of the older population with functional disability. Although the elderly Chinese have a shorter estimated life expectancy, they are expected to spend a smaller proportion of their future lifetime functionally disabled than the elderly Americans. Systematic uncertainty is shown to be significant in future trends in disability rates and our model estimates higher uncertainty in trends for the Chinese elderly, especially for urban residents.

Keywords

functional disability; life expectancy; systematic trend and uncertainty; multi-state latent factor intensity model

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1 Introduction

Longevity improvement and fertility decline around the globe has resulted in an ageing world's population. As the risk of disability increases with age, all countries face the challenges posed by the growing need for long-term care. In China the challenges are exacerbated by dramatic demographic changes that will see a rapid surge in the elderly population who require care and a shrinking working-age population who can provide care.

Long-term care for the Chinese elderly has traditionally been provided by family members. This informal care is becoming less viable with the increasingly common 4-2-1 family structure (consisting of four grandparents, two parents and the only child) and other social-economic changes such as rural-to-urban migration. Amid these changes, private long-term care facilities have expanded rapidly over the past 20 years (Feng et al., 2012). More recently, the Chinese government has piloted public long-term care insurance programs in several cities, preparing for nationwide policy reforms on long-term care (see Feng et al., 2020, for a review).

The shifts in the long-term care landscape mean that the future generations of the elderly in China are likely to be faced with a system closer to the one in the U.S. Since the need for long-term care is largely driven by health status and functional disability, comparing the functional disability and mortality experience between China and the U.S. is important in informing and understanding the development of the long-term care system in China.

Earlier empirical studies on functional disability in China usually draw on cross-sectional data to analyse disability prevalence rates and then use Sullivan's method to estimate disability-free life expectancy. For instance, Liu et al. (2009) use data from two national disability surveys and period life tables finding an upward trend in disability-free life expectancy of the elderly Chinese. Studies that adopt a similar method provide valuable insights into the cross-sectional changes in functional disability at a time when there was limited longitudinal data. These studies do not model health transition dynamics that can incorporate interplay between different health states, age and other individual characteristics.

More recent studies make use of increasingly available longitudinal individual-level data to investigate functional disability in the elderly Chinese population. For example, Hanewald et al. (2019) fit differing generalised linear models for transition rates using the Chinese Longitudinal Healthy Longevity Survey (CLHLS) data stratified by gender and urban-rural residence. Liu et al. (2019) fit logistic models to the transitions for the CLHLS data, using age, sex, urban/rural residence, education as predictor variables and transition probabilities as the dependent variable. The resulting transition probabilities are more relevant than static prevalence rates when estimating future functional disability.

In order to compare China and the U.S. and to understand differing trends and levels in mortality and functional disability, we also use longitudinal individual-level data to estimate health transition rates or probabilities. Since uncertainty is critical in understanding the range of possible future outcomes, we improve earlier studies by incorporating systematic uncertainty

along with time trends in health state transitions. The systematic uncertainty allows us to quantify the risk associated with future disability and mortality. Although some studies have shown the significance of systematic uncertainty in health transitions using U.S. data (Li et al., 2017; Sherris and Wei, 2021), this has not been quantified in the Chinese data.

To quantify the time trend and systematic uncertainty in health transitions among the Chinese elderly and to compare with those in the U.S., we fit a multi-state latent factor intensity model, similar to the one used in Li et al. (2017) and Sherris and Wei (2021). We use the CLHLS data as well as the U.S. Health and Retirement Study (HRS) data for the years between 1998 and 2014 and for the age range 65 and above since we are interested in older ages for long-term care. Li et al. (2017) and Sherris and Wei (2021) assume a random walk process for the latent factor. Based on the empirical plots of the transition rates in Appendix A.1, we test the assumption of a first-order autoregressive, AR(1), process and compare this assumption with the random walk process for the latent factor. We verify that the AR(1) process does not improve the goodness of fit for the CLHLS or HRS data and that assuming a random walk is adequate. We refine the models in Li et al. (2017) and Sherris and Wei (2021) by improving the age change assumption and adjusting for the delay in death reporting. We allow the age covariate to change with each birthday, whereas Li et al. (2017) and Sherris and Wei (2021) update the age covariate value only on the interview dates or when a transition occurs. We consistently use the data collected in later waves to complete the death records for earlier years and thus adjusting for the delay in these earlier years.

One study that is related to ours in respect of the Chinese transition rates is Hanewald et al. (2019). Our modelling approach differs in several aspects apart from incorporating systematic uncertainty. Firstly, they do not include recovery rates from disability in health transitions, whereas we do and, importantly, find a significant time trend in recovery rates. Secondly, we only consider linear age effects in log transition rates, avoiding unrealistic transition rates at older ages and providing a more parsimonious model. Finally, our model is an integrated model based on a stronger statistical foundation. Instead of fitting separate models to different subpopulations stratified by covariates such as gender and residence, we specify a functional form of the transition rate with proportional hazards assumptions, and fit the model using the full sample. This approach not only improves the reliability of the parameter estimation since more data points are employed but also allows us to test the significance of each covariate.

We quantify how both countries experienced longevity improvement with morbidity compression using the longitudinal individual-level data. We estimate that the Chinese elderly have shorter life expectancy but spend a greater proportion of their future lifetime in the healthy state than their U.S. counterparts. Incorporating time trends is important since failing to do so will underestimate both total life expectancy and healthy life expectancy, and overestimate the proportion of the elderly in functional disability in both countries. Incorporating systematic uncertainty allows us to quantify the confidence we have in the estimated proportion in functional disability. We show that the data indicates greater uncertainty in the functional

disability rates for the Chinese elderly.

Within China, we use the model to quantify the significant urban-rural disparity in health and longevity, and show how the gap has widened over time. Urban residents are shown to have reaped more benefits from a longer life expectancy and morbidity compression. Liu et al. (2019) find similar results for those aged 80 and above. We show that this extends to younger ages. We also find that urban residents experience greater health inequity than their rural counterparts. Not only are they subject to greater uncertainty in their survival probability, but the proportion of people with functional disability has a heavier-tailed distribution.

The rest of the paper is structured as follows. Section 2 introduces the health transition model and the estimation method. Section 3 describes the data with an exploratory data analysis. Section 4 discusses the estimation results. Section 5 compares our model results with other studies and population data. Section 6 provides a comparison of our model results and forecasts between China and the U.S. Section 7 concludes.

2 Health State Transition model

Since long-term care insurance benefits are paid when the policyholder is disabled and cease when the policyholder recovers or dies, we use a three-state Markov process to model the health state transitions. The three states are healthy (H), functionally disabled (F) and dead (D). The health state is determined by a person's ability to perform activities of daily living (ADLs). The definition is in line with common practice used by insurers. In both the CLHLS and the HRS, there are six ADLs, and they only differ by one ADL.[1] Most long-term care insurance policies pay benefits when the policyholder needs help in two or more ADLs or has a cognitive impairment (Administration for Community Living, 2020). The CLHLS and the HRS have different measures for cognitive function, making it hard to compare, so we use the ADLs alone to define disability. An individual needing help in two or more ADLs is in State F. We also allow for recovery from the disabled state to the healthy state. Figure 1 illustrates the transition model.

We assume a Markov model. The Markov process is widely used in the literature to model health state transitions (see e.g. Fong et al., 2015; Ameriks et al., 2011). Although the Markovian property does not take into account the past transitions or the time spent in the previous states, the model achieves satisfactory goodness of fit and is more computationally efficient than the semi-Markov process (see e.g. Møller, 1992; Haberman and Pitacco, 1998; Leveille et al., 2000; Wolthuis, 2003).

We use a Cox proportional hazard model (Cox, 1972) for each transition intensity. Some recent applications of the model include Koopman et al. (2008) on credit rating migrations and Li et al. (2017) on health state transitions. The transition intensity for individual k of transition

[1]The five common ADLs are bathing, toileting, dressing, indoor transferring, and feeding. The sixth ADL is continence in the CLHLS, and getting in/out of bed in the HRS.

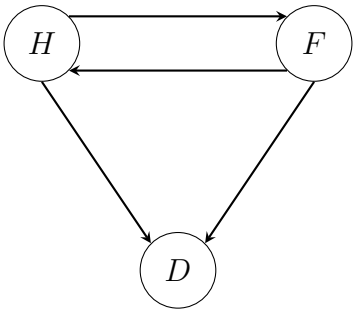

Figure 1. The health state transition model.

type s ($s \in \{1, 2, 3, 4\}$ where $s = 1$ denotes $H \to F$, $s = 2$ denotes $F \to H$, $s = 3$ denotes $H \to D$, $s = 4$ denotes $F \to D$) at time t is given by

$$\lambda_{k,s}(t) = \exp[\beta_s + \boldsymbol{\gamma}_s' \cdot \boldsymbol{\omega}_k(t) + \alpha_s \cdot \psi(t)] \cdot H_{k,s}(t). \tag{1}$$

The vector $\boldsymbol{\omega}_k(t)$ contains observable explanatory covariates, such as age, gender and time. The process $\psi(t)$ is an unobservable (or latent) factor, also referred to as frailty, that captures the randomness of the transition intensity. It affects all transition types, thus generating systematic risk. The scalar β_s, the vector $\boldsymbol{\gamma}_s$ and the scalar α_s are fixed unknown coefficients. The β_s term is the reference-level log-intensity of transition type s in the starting year. It remains the same across time and individuals. The parameters $\boldsymbol{\gamma}_s$ and α_s measure, for transition type s, the sensitivity of the log-intensity to the observable covariates $\boldsymbol{\omega}_k(t)$ and the latent factor $\psi(t)$, respectively. The scalar function $H_{k,s}(t)$ is the underlying baseline hazard function to allow for duration dependence (Koopman et al., 2008). For example, $H_{k,s}(t)$ can be specified as $H_{k,s}(t) = H_s(t - t_k)$ where $(t - t_k)$ denotes the backward-recurrence time of the k^{th} individual with respect to his/her last transition moment. More choices for $H_{k,s}(t)$ can be found in Koopman et al. (2008). We assume the Markovian property, so $H_{k,s}(t)$ is a constant. Without loss of generality, we set $H_{k,s}(t)$ to be 1.

The data from both the CLHLS and the HRS is collected every two to three years. We use t_j, measured in years, to denote the time of the j^{th} interview and denote $\psi_j = \psi(t_j)$ as the value of $\psi(t)$ over the interval $t \in (t_{j-1}, t_j]$. Plotting the crude transition rates against time suggests possible autoregression in the transition rates (see Appendix A.1 for the plots). The lines show a zigzag pattern in that an increase in the transition rate is often followed by a decrease and vice versa. To capture the possible serial correlation in ψ_j, we assume ψ_j follows a first-order autoregressive process, or an AR(1) process, with

$$\psi_j = \rho^{t_j - t_{j-1}} \psi_{j-1} + \varepsilon_j, \quad \varepsilon_j \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_j^2), \quad \psi_0 = 0. \tag{2}$$

We use a heteroscedastic normal error term because the time between consecutive interview waves is not constant and hence the error term needs to account for this. $|\rho| \leq 1$ is the autoregressive parameter. When $\rho = 1$, ψ_j becomes a random walk process. Since not all α_s in Equation (1) and σ_j can be identified simultaneously (Koopman et al., 2008), we normalise σ_j

to

$$\sigma_j^2 = \begin{cases} \dfrac{1-\rho^{2(t_j - t_{j-1})}}{1-\rho^2} & \text{if } -1 < \rho < 1, \\ t_j - t_{j-1} & \text{if } \rho = 1. \end{cases} \tag{3}$$

We consider the following three models in the parameter estimation.

1. Static model

$$\ln \lambda_{k,s}(t) = \beta_s + \gamma_s^{\text{age}}\, x_k(t) + \gamma_s^{\text{female}}\, F_k, \tag{4}$$

   where $x_k(t)$ represents the age for the the k^{th} individual at time t and $F_k = 1$ if the k^{th} individual is female.

2. Trend model

$$\ln \lambda_{k,s}(t) = \beta_s + \gamma_s^{\text{age}}\, x_k(t) + \gamma_s^{\text{female}}\, F_k + \gamma_s^{\text{time}}\, t, \tag{5}$$

   where t captures the time trend.

3. Frailty model

$$\ln \lambda_{k,s}(t) = \beta_s + \gamma_s^{\text{age}}\, x_k(t) + \gamma_s^{\text{female}}\, F_k + \gamma_s^{\text{time}}\, t + \alpha_s\, \psi(t), \tag{6}$$

   where $\psi(t)$ is the frailty factor defined in Equation (2).

The covariates $x_k(t)$ in Equations (4) to (6), and t in Equations (5) to (6), are scaled, so their values are within the same order of magnitude as the gender indicator, F_k. This helps to improve the numerical stability in the estimation. We follow Yogo (2016) to set the age covariate $x_k(t)$ to $\frac{x_k^{\text{last}}(t)-65}{10}$ where $x_k^{\text{last}}(t)$ represents the age last birthday. In a similar vein, the time covariate t is set to $\frac{Time}{10}$, where $Time$ is based on the year-year range that is determined by the interview waves (Table 1).

We improve the estimation in earlier studies (see e.g. Li et al., 2017), by avoiding directly using the interview waves as the time covariate due to the delay in death reporting, which is a known issue for survey data not linked to the national death index. The delay happens if someone died shortly after the interview, and the death was not reported until the next interview wave. As a result, deaths that occur in the same year (especially when it is a survey year) can be reported in different waves.[2] Using the calendar year instead of the interview waves ensures consistency within deaths and between different types of health transitions when assigning values to the time variable.

Prior studies have shown large urban-rural disparities in the health care system (Hougaard et al., 2011), spending on long-term care (Li et al., 2013), as well as disability and mortality rates in China (Hanewald et al., 2019). Given the significance of the urban-rural disparity in China, we also consider residence as a covariate when fitting to the CLHLS data. The log transition

[2]See Appendix A.2 for the number of deaths recorded in each wave.

Table 1. The correspondence between year and *Time*.

CLHLS		HRS	
Year	*Time*	Year	*Time*
1998 – 1999	1	1998 – 1999	1
2000 – 2001	3	2000 – 2001	3
2002 – 2004	5	2002 – 2003	5
2005 – 2007	8	2004 – 2005	7
2008 – 2010	11	2006 – 2007	9
2011 – 2013	14	2008 – 2009	11
2014	17	2010 – 2011	13
		2012 – 2013	15
		2014 – 2015	17

intensity in the frailty model becomes

$$\ln \lambda_{k,s}(t) = \beta_s + \gamma_s^{\text{age}}\, x_k(t) + \gamma_s^{\text{female}}\, F_k + \gamma_s^{\text{resid}}\, U_k + \gamma_s^{\text{time}}\, t + \alpha_s\, \psi(t), \tag{7}$$

where $U_k = 1$ if the k^{th} individual lived in city or town when joining the survey. We choose the residence status at the point of joining the survey because this choice is assumed to reflect the place where the individuals spent most of their lifetime. Figure 2 shows that around 20% of health transitions involve a change of residence. This proportion is relatively small and varies little with the type of health transitions.

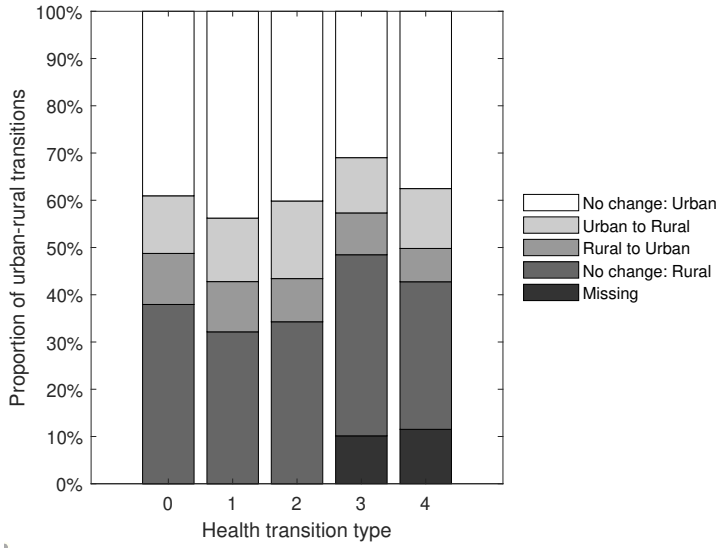

Figure 2. The distribution of change of residence that occurred in each type of health state transitions based on the selected CLHLS sample. Health transition type 0 means there is no change of health states. Health transition type 1 denotes healthy to disabled, 2 disabled to healthy, 3 healthy to dead, 4 disabled to dead.

We use maximum likelihood estimation (MLE) to estimate the parameters. We define two indicator functions, $Y_{k,s,j}$ and $R_{k,s}(t)$. $Y_{k,s,j} = 1$ if transition type s is observed between the j^{th} and the $(j+1)^{\text{th}}$ interviews, and $R_{k,s}(t) = 1$ if the individual is exposed to the risk of transition

type s at time t. If any type of transition occurs, we use $\hat{t}_j$ to denote the time of transition. For a total of S transition types, K individuals and J interview waves, the likelihood function conditional on the complete path of the frailty is given by

$$L(\boldsymbol{\theta}|\mathcal{F}_J, \Psi)$$
$$= \prod_{j=1}^{J-1} \prod_{k=1}^{K} \prod_{s=1}^{S} \exp\left\{ Y_{k,s,j} \ln \lambda_{k,s}(\hat{t}_j) - R_{k,s}(t_j) \int_{t_j}^{\hat{t}_j} \lambda_{k,s}(u)\mathrm{d}u - R_{k,s}(\hat{t}_j) \int_{\hat{t}_j}^{t_{j+1}} \lambda_{k,s}(u)\mathrm{d}u \right\}, \quad (8)$$

where $\boldsymbol{\theta}$ denotes the set of parameters to be estimated, $\mathcal{F}_J$ denotes all the information available up to time t_J, $\Psi = \{\psi(t_j) : j = 0, 1, \cdots, J\}$. The integrals in Equation (8) incorporate changes of age and time. Integrating over the path of Ψ gives the likelihood function that is unconditional on Ψ

$$L(\boldsymbol{\theta}|\mathcal{F}_J) = \int L(\boldsymbol{\theta}|\mathcal{F}_J, \Psi)\mathrm{d}P(\Psi). \quad (9)$$

It is computationally intensive to evaluate Equation (9) due to the high dimension of the integral. We use a Monte Carlo simulation technique to reduce the computational burden. We first simulate M paths of Ψ denoted by $\Psi^{(1)}, \cdots, \Psi^{(M)}$. The likelihood function $L(\boldsymbol{\theta}|\mathcal{F}_J)$ is then estimated as

$$\hat{L}(\boldsymbol{\theta}|\mathcal{F}_J) = \frac{1}{M} \sum_{m=1}^{M} L(\boldsymbol{\theta}|\mathcal{F}_J, \Psi^{(m)}). \quad (10)$$

We use the quasi-Newton method to find the parameter estimates. In each iteration, the same random numbers are used to simulate the M paths of Ψ. This ensures a smooth likelihood surface. The estimation procedure is implemented in MATLAB using the `fminunc` function, which applies to an unconstrained function. When the autoregressive parameter (ρ) is estimated, the optimisation problem becomes a constrained one due to the stationarity condition. To continue using the `fminunc` function, we use the algorithm in Jones (1980) to transform the constrained optimisation procedure to an unconstrained one. The algorithm maps a real-valued parameter to the stationarity region. Once the parameters are estimated, we use the Kalman filtering and smoothing technique to recover the frailty process. Sherris and Wei (2021) give a detailed procedure. The code is available at `https://sites.google.com/view/mxu/code` for download.

3 Exploratory Data Analysis on the CLHLS and HRS

3.1 Data description

To compare China and the U.S., we use the CLHLS (Zeng et al., 2017) and the HRS (Health and Retirement Study, 2020; RAND HRS Longitudinal File 2016 (V2), 2020) to estimate the model parameters. Both datasets have a similar structure, containing one record (i.e. one row of a spreadsheet) for each interviewee, who is identified by a unique identity number. Each record consists of multiple variables (i.e. columns of a spreadsheet), including date of birth,

gender, interview wave, difficulty in the activities of daily living. A full list of variables selected for our analysis can be found in Appendix A.3.

The CLHLS started in 1998 and conducts face-to-face interviews every two to three years in 22 provinces, representing 85% of the population in mainland China (Zeng, 2004). The survey originally sampled individuals aged 80 and above, and has expanded to those aged 65 and above since 2002. We use the datasets from 1998 to 2014, which is the latest survey available. The HRS is a biennial survey of initially non-institutionalised Americans over age 50. The survey started in 1992, but the early waves contain some inconsistency in the survey questions about ADLs (Fong et al., 2015). To bring age and year ranges in line with those in the CLHLS, we use the HRS data from 1998 to 2014 and exclude individuals who had not reached 65 by 2014.

The transitions between healthy and disabled states are interval-censored. We assume the transition occurred in the midpoint of the two interview dates and limit the sample to those whose identity numbers appeared in consecutive waves. The time of death is recorded, but there is a delay in death reporting, as explained in Section 2 so we argue for using the calendar year rather than interview wave as the time covariate. As the delay in death reporting, if it occurs, is at most one interview wave, for years prior to the last interview wave, we use the information from later waves to complete the death records. We cannot do this correction in reporting for the last wave (i.e. year 2014) since the death data in later waves is yet to be collected. We therefore remove the health transitions that occurred in 2014 to avoid bias. After further removing those with missing interview dates, missing or invalid death dates (e.g. February 29^{th} in non-leap years), or missing information on ADLs, we are left with 36,233 individuals in the CLHLS sample and 22,467 individuals in the HRS sample. The selected HRS sample has fewer individuals but more interview waves. The summary statistics of the two selected samples are presented in Appendix A.4.

Figure 3 shows the proportion of health state transitions at each age for the selected CLHLS sample and HRS sample. The health transitions of the selected CLHLS sample are dominated by deaths, while those of the HRS sample are more evenly spread across different transition types except for the very advanced ages. Figure 4 compares the total person-years at risk between the two samples. The HRS sample shows a downward trend with age, whereas the CLHLS sample shows an inverse U shape. The differences in the health transition and exposure between the two samples are mainly due to different sampling ages. The CLHLS sample has more participants of the middle-old and the oldest-old than the HRS. Despite those differences, both samples contain a sufficiently large number of individuals in each age group above 65 for our model estimation. Given the differences in the absolute values of person-years at risk, we plot the proportion of person-years at risk in healthy and disabled states in Figure 5. Compared to the HRS sample, the CLHLS sample has a higher proportion of person-years at risk in the healthy state and it decreases at a slower rate with age.

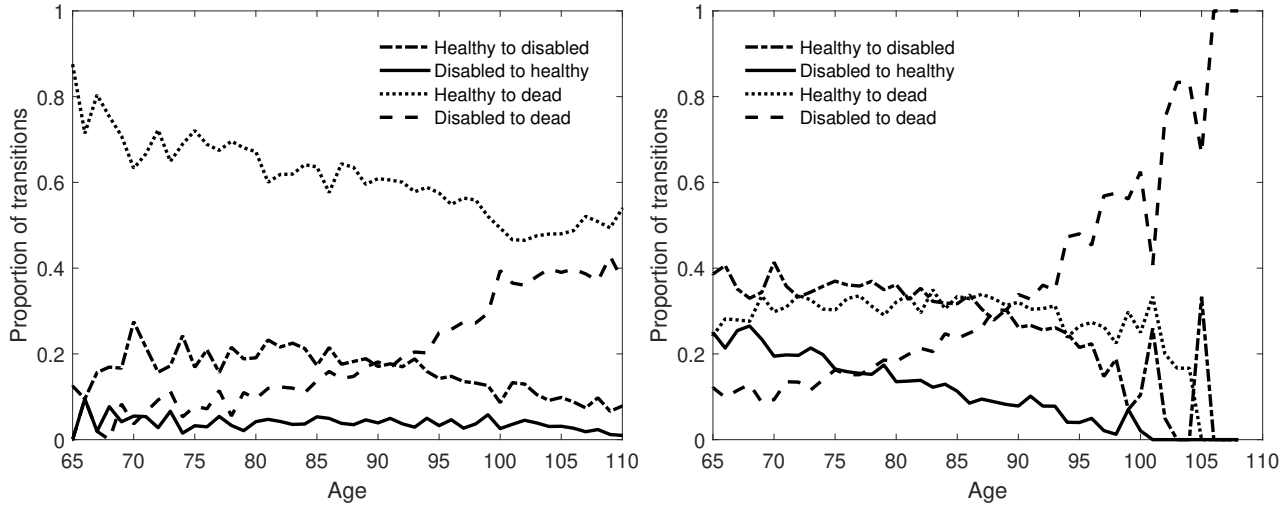

Figure 3. Proportion of transitions between different health states for (Left Panel) the selected CLHLS sample and (Right Panel) the selected HRS sample.

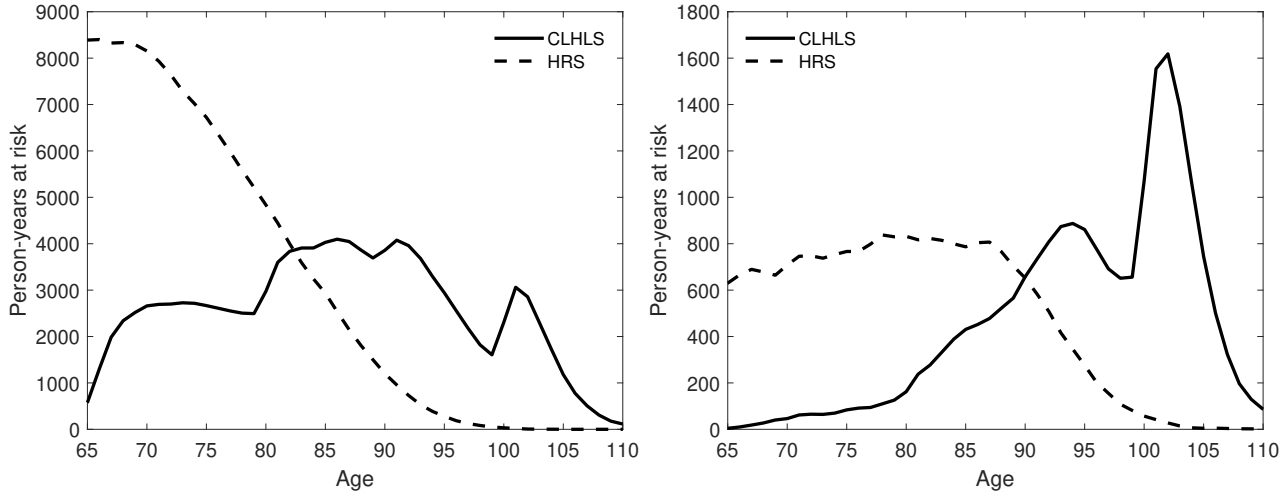

Figure 4. Total person-years at risk in (Left Panel) healthy and (Right Panel) disabled states for the selected CLHLS sample and HRS sample.

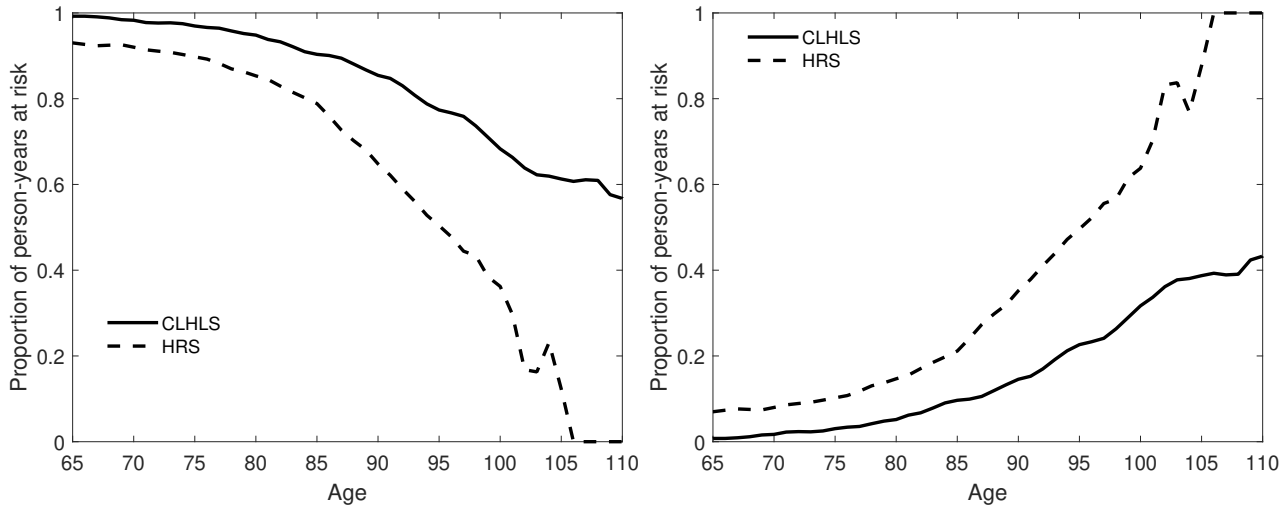

Figure 5. Proportion of person-years at risk in (Left Panel) healthy and (Right Panel) disabled states for the selected CLHLS sample and HRS sample.

3.2 Proportional hazard assumption

We make the proportional hazard assumption when defining the transition intensity in Equation (1). In this section we use a graphical approach to evaluate this assumption. Figure 6 plots the crude health transition rates by age. There are four curves in each panel, representing each gender in each of the two samples. The two curves that correspond to female and male transition rates in a given sample are seen to be reasonably parallel in that they do not cross over or diverge. In addition, the log transition rates show a linear trend with age in almost all transition types, supporting our model assumption to have a linear age term in the transition intensity. We also plot the crude transition rates by urban-rural residence in the CLHLS sample, shown in Appendix A.5, and confirm the reasonableness of the proportional hazard assumption. In summary, the graphical checks support these assumptions in our model specification. Model estimation results are in the next section.

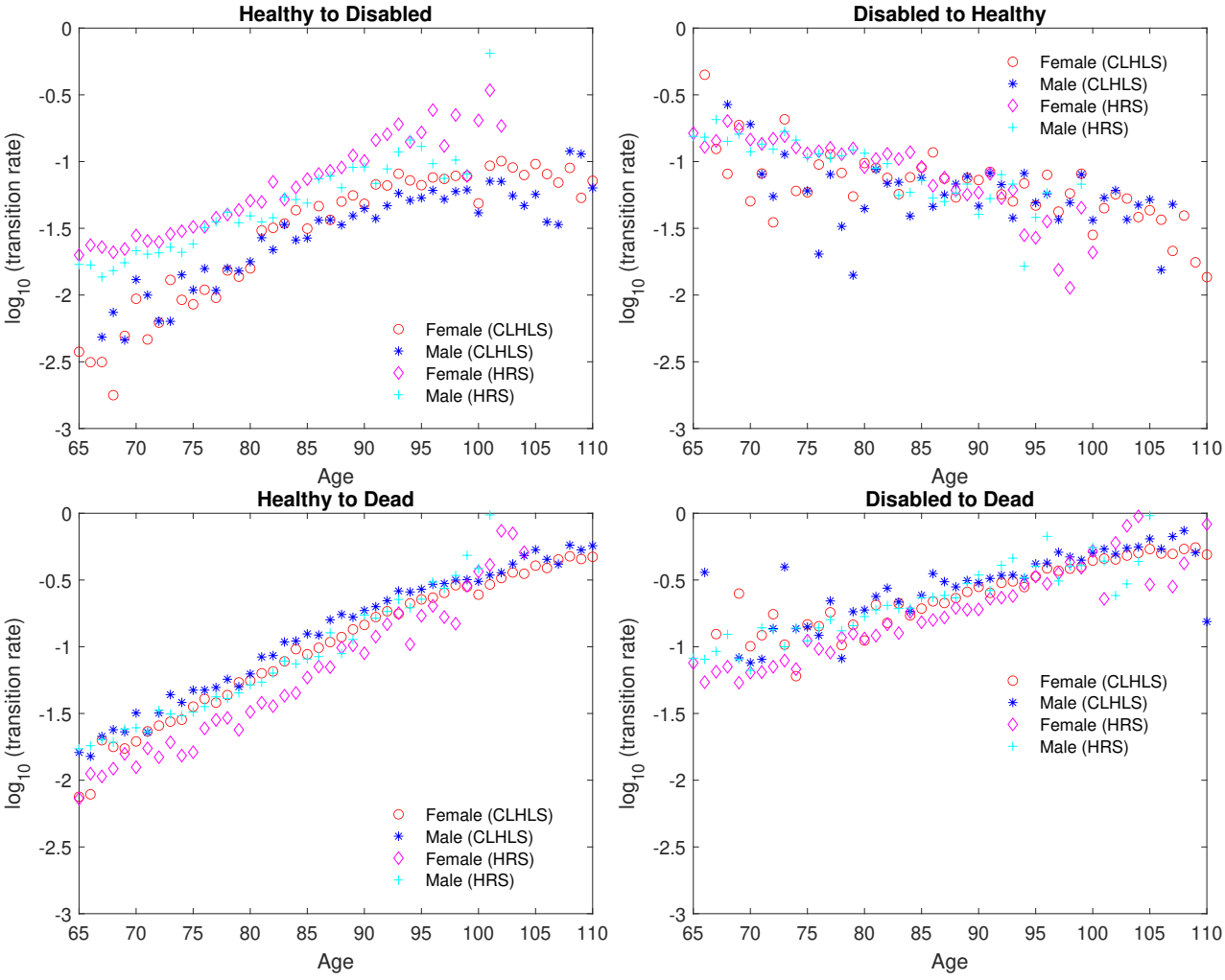

Figure 6. Crude health transition rates by age for female and male.

4 Estimating the Health Transition Model

We use the MLE to estimate the transition model parameters, and this section discusses the estimation results. Since the computation time for estimating the frailty model can be much longer, and this model feature is an important contribution we make to functional disability transition modelling, we first report the computational time and compare the goodness of fit of the static, trend and frailty models in Section 4. Section 5 validates the estimation results.

We then simulate the heath state transitions using the estimated transition models to determine life expectancy, including healthy life expectancy, as well as disability prevalence, implied by the model and discuss the simulation results in Section 6 with 6.1 comparing China and U.S. life expectancy and 6.3 considering urban-rural differences in China.

Estimating the static and trend models is computationally efficient. It can be completed within minutes on a standard desktop. Estimating the frailty model requires substantially more computational resources. We show that the running time is not unwieldy and allows for the application of the model to the individual longitudinal data we have (Table 2).

Table 2. Approximate running time of the frailty model, where the latent factor is modelled as a random walk process or an AR(1) process. The code is implemented in MATLAB Release 2019b.

Model	Number of parameters	Running time (hour)
CLHLS		
Random walk	20	11
AR(1)	21	16
CLHLS with residence		
Random walk	24	27
AR(1)	25	30
HRS		
Random walk	20	16
AR(1)	21	20

Note: The computational time is based on 1,000 simulated frailty paths and 12 CPU cores.

We use the likelihood ratio test to determine whether each of the following improves the model fit: *1*) adding the time trend to the static model, *2*) adding the frailty factor to the trend model, *3*) relaxing the constraint on the autoregressive parameter. The likelihood ratio test statistic is given by

$$-2\ln\left(\ell_{\text{null}} - \ell_{\text{alternative}}\right),$$

where ℓ_{null} is the maximum log-likelihood of the model under null hypothesis, and $\ell_{\text{alternative}}$ is the maximum log-likelihood of the model under alternative hypothesis. Under the null hypothesis, the test statistic asymptotically follows a chi-squared (χ^2) distribution with degrees of freedom equal to the difference in the number of parameters between the null and alternative hypotheses.

Table 3 shows that adding the time trend to the static model and adding the frailty factor to the trend model significantly improve the model fit. By contrast, the additional autoregressive parameter, that was considered to capture the time series behavior of the transition rates and improve the latent process, does not improve the goodness of fit. A random walk assumption for the latent process is adequate.

Table 3. Test statistics of the likelihood ratio tests. Frailty (RW) means the latent process is modelled as a random walk process. Frailty (AR) means the latent process is modelled as an AR(1) process.

	Pair of models (null vs. alternative)		
	Static vs. Trend	Trend vs. Frailty (RW)	Frailty (RW) vs. Frailty (AR)
CLHLS	355^{***}	354^{***}	2
CLHLS with residence	339^{***}	361^{***}	2
HRS	78^{***}	43^{***}	0

Note: $^{***}p < 0.01$, $p > 0.1$ otherwise.

We also compute the Akaike information criterion (AIC) and Bayesian information criterion (BIC) to verify the likelihood ratio test results. The two information criteria are given by

$$\text{AIC} = 2\kappa - 2\ell, \quad \text{BIC} = \kappa \ln(n) - 2\ell,$$

where κ is the number of estimated parameters in the model, ℓ the maximum log-likelihood of the model, n the number of observations. A lower value of AIC or BIC implies a better fit. Table 4 shows that AIC and BIC results draw the same conclusion with the likelihood ratio test. In the light of the goodness of fit test results, the frailty model assumes a random walk process in the rest of the paper.

Table 4. Akaike information criterion (AIC) and Bayesian information criterion (BIC) of each model. Frailty (RW) means the latent process is modelled as a random walk process. Frailty (AR) means the latent process is modelled as an AR(1) process.

Model	CLHLS		CLHLS with residence		HRS	
	AIC	BIC	AIC	BIC	AIC	BIC
Static	169,046	169,169	168,916	169,081	135,899	136,029
Trend	168,699	168,864	168,585	168,790	135,829	136,002
Frailty (RW)	168,353	168,559	168,231	168,478	135,794	136,011
Frailty (AR)	168,353	168,569	168,231	168,488	135,794	136,011

5 Model Reasonableness: Comparison with Other Studies and Population Data

We now assess the reasonableness of the estimation results by comparing *1*) the fitted transition rates to the crude ones as well as prior literature, *2*) the estimated life expectancy to external sources. Since the life expectancy is derived from the transition rates, we focus on comparing the fitted rates. The comparison of life expectancy can be found in Appendix B.

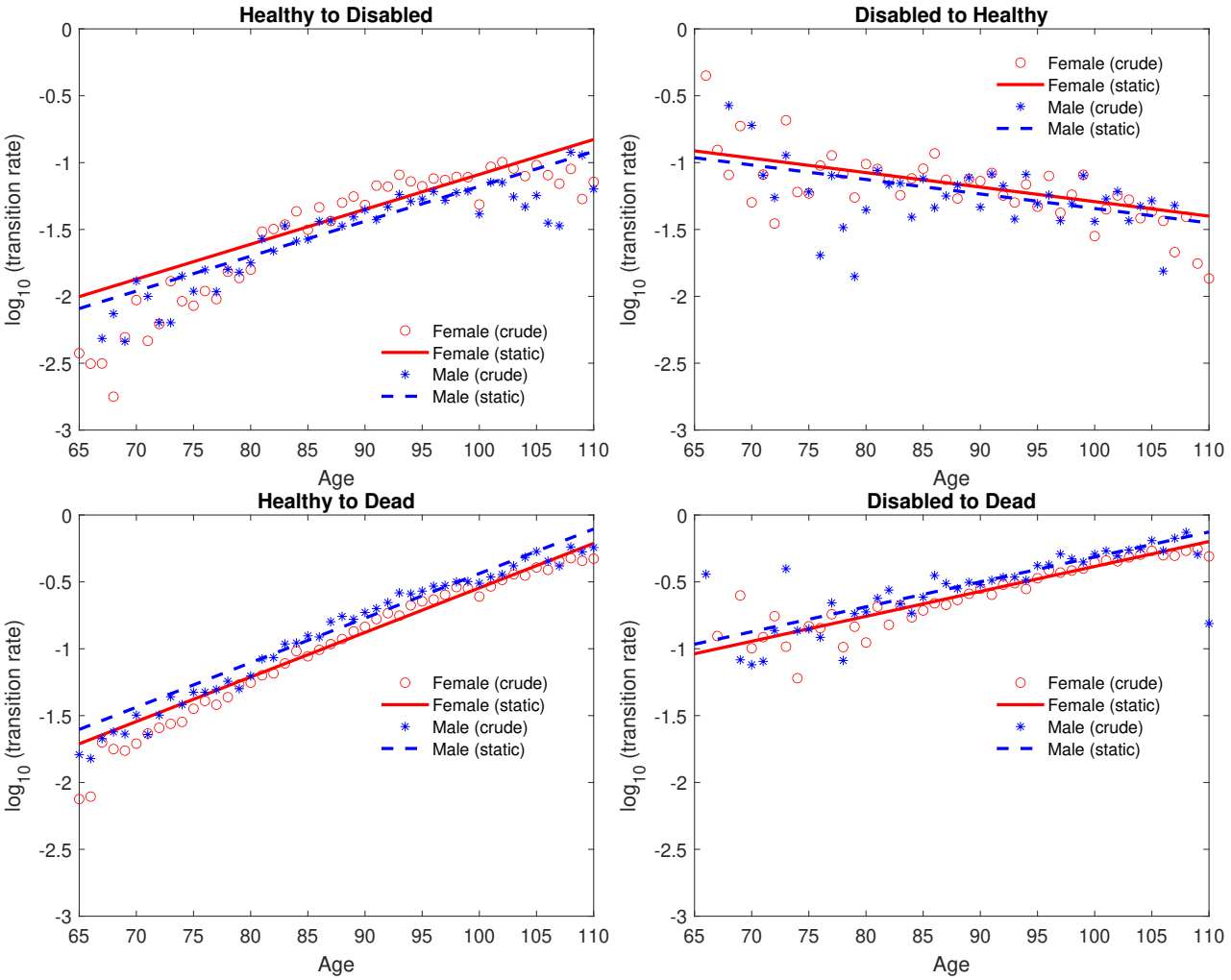

Figure 7. Static model: estimated transition rates compared to the crude rates based on the selected CLHLS sample.

We first compare the fitted transition rates from the static model to the crude rates. Figure 7 and Figure 8 plot the fitted static rates along with the crude rates based on the CLHLS sample and the HRS sample, respectively. The fitted rates can be seen to correspond closely with the crude ones, demonstrating a satisfactory model fit. For the CLHLS sample, the crude disability rates (top left panel of Figure 7), on the logarithmic scale, show some curvature, whereas the model assumes a linear age effect. Liu et al. (2019) include a quadratic age term that is not statistically significant at a 95% confidence level when modelling annual transition probabilities based on the CLHLS data in a logistic model. In our logarithmic model, as given in Equation (4), we assume a linear age effect, which may overstate disability rates at the very

old ages.

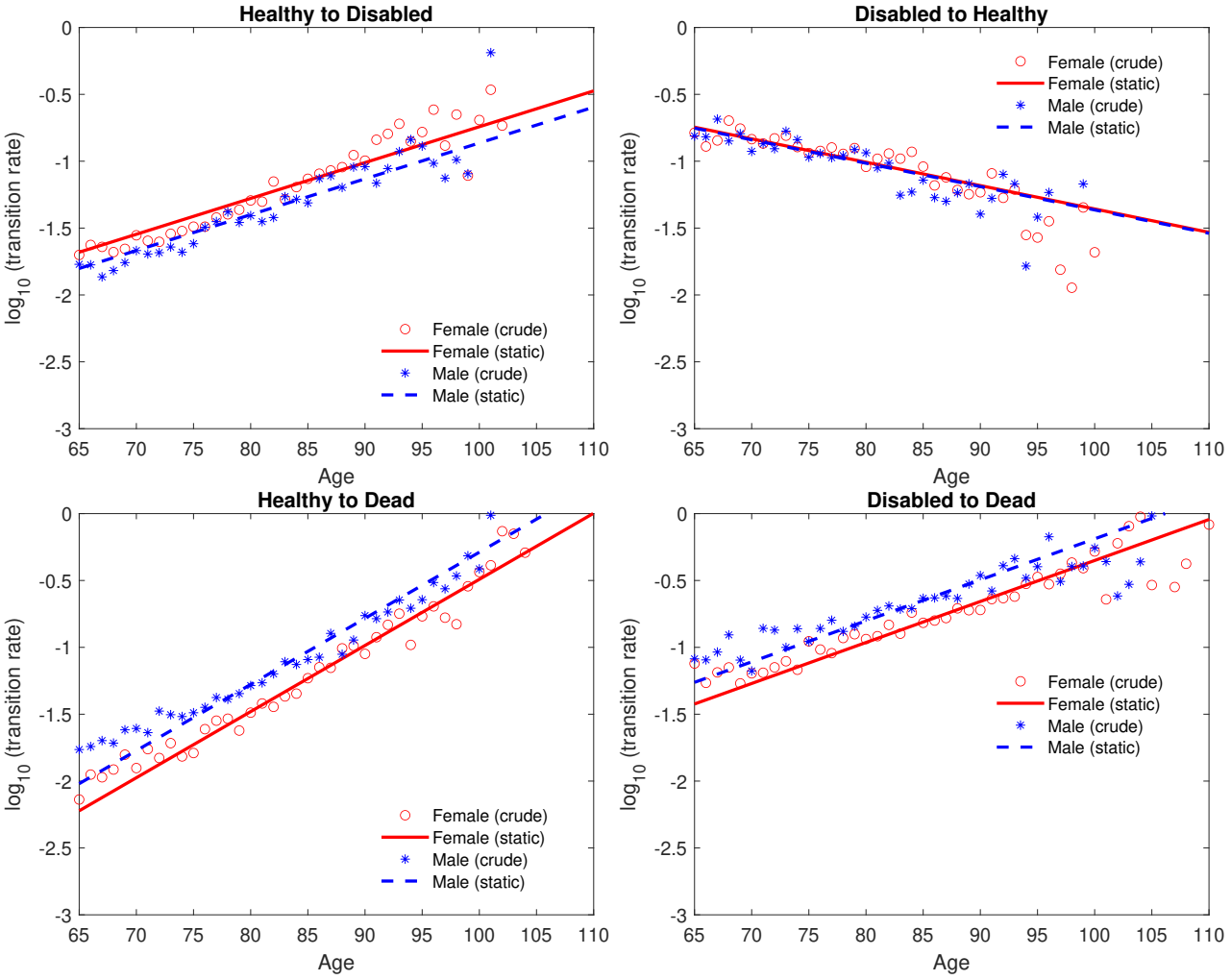

Figure 8. Static model: estimated transition rates compared to the crude rates based on the selected HRS sample.

Our models are not fitted to the crude rates since, we fit our functional form of the transition rate that includes age and gender as covariates, also with time trends, using the individual-level observations. To compare our estimated transition rates from the static model with no time trends, we compare with the crude rates from the full dataset based on number of transitions and person-years of exposures. To assess the transition rates with time trend, we compare our fitted rates to those with time trends and the same set of covariates in prior literature. In particular, we compare our fitted transition rates with those computed with the estimated parameter values in Li et al. (2017), Hanewald et al. (2019) and Sherris and Wei (2021).Table 5 shows that these papers use the same data source and similar sample periods.

Table 5. Comparison of data sources and their sample periods.

	Data		Sample Period
	HRS*	CLHLS†	
Li et al. (2017)	X		1998 – 2012
Hanewald et al. (2019)		X	1998 – 2012
Sherris and Wei (2021)	X		1998 – 2014
Our study	X	X	1998 – 2014

* HRS stands for U.S. Health and Retirement Study.
† CLHLS stands for Chinese Longitudinal Healthy Longevity Survey.

Figure 9 compares the fitted rates with those in Hanewald et al. (2019) based on the CLHLS sample. Hanewald et al. (2019) fit separate models for different transition rates and for individuals in each gender and residence category and include a time trend. We use our fitted rates from the trend model with the residence covariate for comparison. Figure 9 shows that the results are broadly comparable with only differences in the disability rates (the four panels in the top row). The difference is caused by the quadratic age term included in Hanewald et al. (2019). For all our transition rates we assume only a linear age effect in logarithmic transition rates. At older ages our model may overstate disability rates for China although the crude rates in Figure 7 shows this only occurs for the Chinese data.

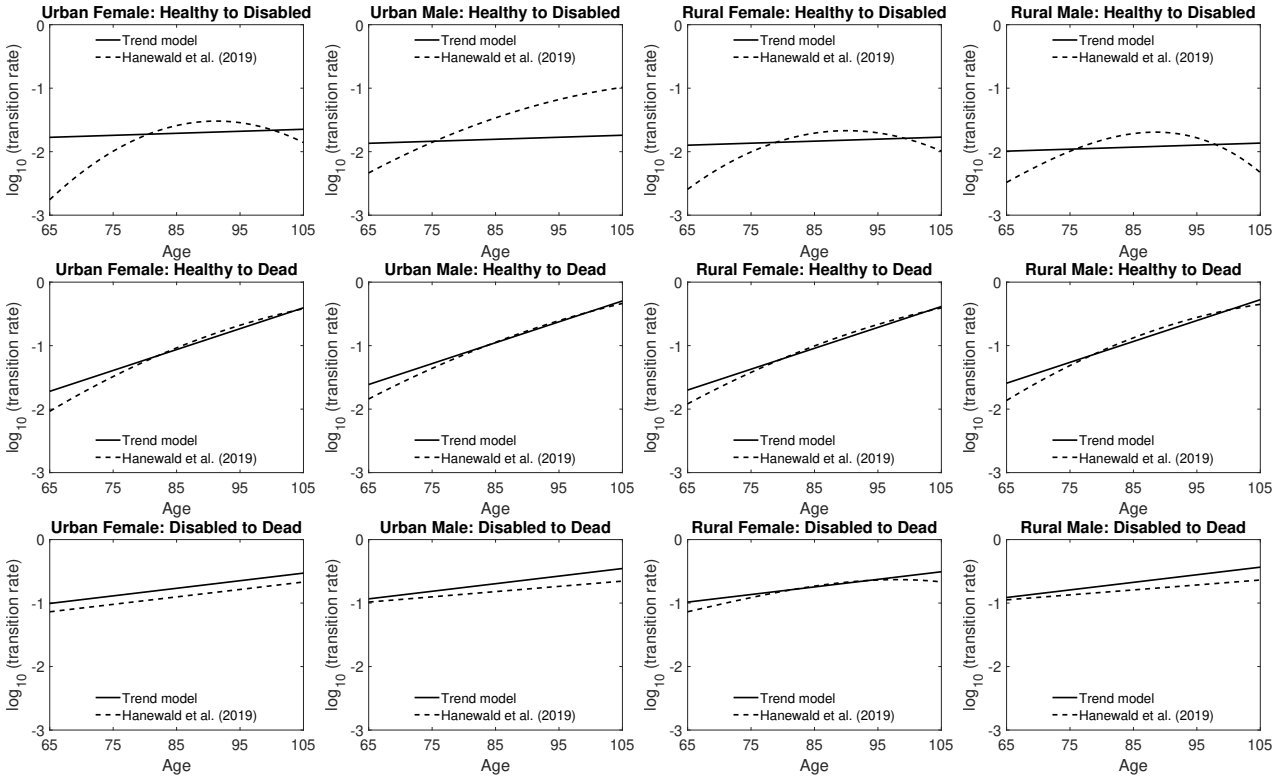

Figure 9. Trend model with residence: estimated transition rates compared to the fitted rates in Hanewald et al. (2019) for a cohort of Chinese who were 65 in 1998.

Figure 10 compares the fitted rates with those in Li et al. (2017) and Sherris and Wei (2021) for females based on the HRS data. The comparison for males is given in Appendix B, and the results are similar to those for females. The top row of Figure 10 shows that the fitted rates from the static model align well with prior literature. There are small differences in the mortality rates, especially at younger ages (the two panels on the right in the top row of Figure 10). As discussed earlier, our improved model estimation provides more accurate estimates of these rates. The reason for this is that we allow the age covariate to change with each birthday, whereas Li et al. (2017) and Sherris and Wei (2021) update the age covariate value on the interview dates or when a transition occurs. Improving the age change assumption shifts deaths to younger ages, leading to higher mortality at these younger ages as seen in the figures.

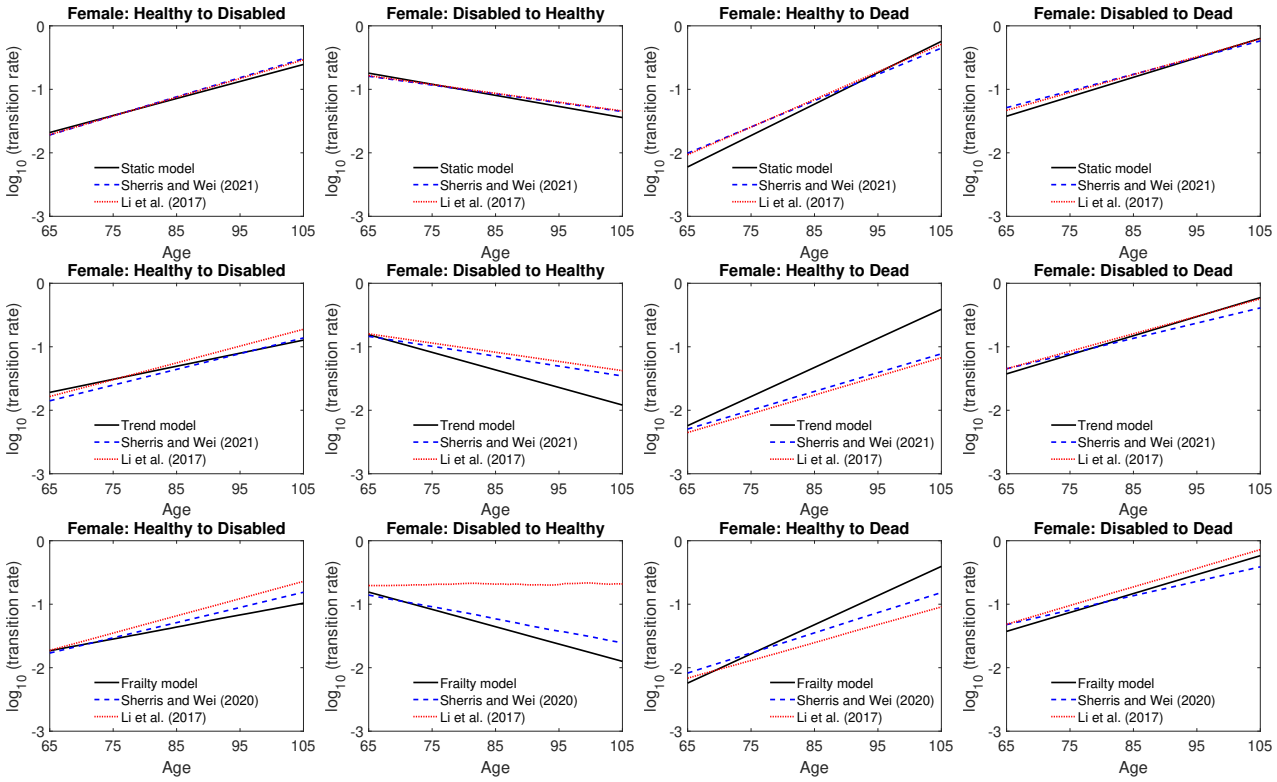

Figure 10. Static (first row), trend (second row) and frailty (last row) models: estimated transition rates compared to the fitted rates in Li et al. (2017) and Sherris and Wei (2021). The average transition rate is shown for the frailty model. The rates apply to a cohort of females in the U.S. who were 65 in 2010.

The two panels on the right in the bottom two rows of Figure 10 show our estimates have a faster increase in mortality with age compared to Li et al. (2017) and Sherris and Wei (2021). Since we take into account the delay in death reporting and define the time covariate based on calendar years rather than interview waves, deaths are counted in earlier years, resulting in a faster increase in mortality with age for a cohort.

Figure 10 also shows a noticeable difference in the recovery rates of the trend and frailty models between our results and those in Li et al. (2017) and Sherris and Wei (2021). The difference reflects the higher level of systematic uncertainty in the recovery rates estimated in Li et al. (2017) and Sherris and Wei (2021). Table 6 shows that their estimated time trend coefficients of recovery rate ($\hat{\gamma}_2^{\text{time}}$) are more sensitive to the frailty factor. After including the frailty factor, $\hat{\gamma}_2^{\text{time}}$ changes almost tenfold in Li et al. (2017) and close to fivefold in Sherris and Wei (2021). Our improved estimation of trends and uncertainty produces more accurate estimates of recovery rates.

Table 6. Comparing the estimated time coefficient ($\hat{\gamma}_s^{\text{time}}$) in the trend and frailty models.

Transition Type	$H \to F$	$F \to H$	$H \to D$	$F \to D$
$s =$	1	2	3	4
Trend	-0.1519***	-0.2513***	-0.0865***	-0.0146
Frailty	-0.2120***	-0.2432***	-0.0842***	-0.0201
Li et al. (2017)				
Trend	-0.0143**	-0.0025	-0.0674***	-0.0029
Frailty	-0.0117	0.0243**	-0.0777***	0.0036
Sherris and Wei (2021)				
Trend	-0.0276***	-0.0089**	-0.0605***	-0.0118***
Frailty	-0.0321***	-0.0387***	-0.0511***	-0.0194***

Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. The estimated coefficients values in our models are not directly comparable to Li et al. (2017) and Sherris and Wei (2021) because the time covariate is defined differently.

We have shown how our estimated transition rates compared with the estimated rates in prior literature and explained the differences in terms of model assumptions. The full details of the estimated parameter values are given in Table 7 to Table 9.

We now use the estimated parameters to simulate health transitions in order to estimate implied survival curves and future life expectancy allowing for improvement trends and uncertainty. We compare the Chinese and U.S. results and discuss implications.

Table 7. Static model: estimated parameters with standard errors in parentheses.

Transition Type	$H \to F$	$F \to H$	$H \to D$	$F \to D$
$s =$	1	2	3	4
China (CLHLS)				
$\hat{\beta}_s$	-4.8152***	-2.2187***	-3.6924***	-2.2249***
	(0.0447)	(0.0999)	(0.0243)	(0.0517)
$\hat{\gamma}_s^{\text{age}}$	0.6012***	-0.2496***	0.7669***	0.4294***
	(0.0151)	(0.0337)	(0.0082)	(0.0158)
$\hat{\gamma}_s^{\text{female}}$	0.2054***	0.1180**	-0.2473***	-0.1641***
	(0.0313)	(0.0660)	(0.0157)	(0.0258)
Log likelihood	-84,511			
China (CLHLS) with residence				
$\hat{\beta}_s$	-4.91***	-2.0940***	-3.6722***	-2.1977***
	(0.0474)	(0.1039)	(0.0252)	(0.0532)
$\hat{\gamma}_s^{\text{age}}$	0.6080***	-0.2561***	0.7659***	0.4280***
	(0.0151)	(0.0337)	(0.0082)	(0.0158)
$\hat{\gamma}_s^{\text{female}}$	0.2130***	0.1081*	-0.2485***	-0.1663***
	(0.0313)	(0.0660)	(0.0157)	(0.0258)
$\hat{\gamma}_s^{\text{urban}}$	0.3096***	-0.2387***	-0.0457***	-0.0490**
	(0.0295)	(0.0596)	(0.0158)	(0.0227)
Log likelihood	-84,442			
U.S. (HRS)				
$\hat{\beta}_s$	-4.1488***	-1.7334***	-4.6496***	-2.9050***
	(0.0247)	(0.0320)	(0.0298)	(0.0417)
$\hat{\gamma}_s^{\text{age}}$	0.6171***	-0.4023***	1.1385***	0.7059***
	(0.0129)	(0.0161)	(0.0155)	(0.0179)
$\hat{\gamma}_s^{\text{female}}$	0.2799***	0.0169	-0.4672***	-0.3729***
	(0.0262)	(0.0369)	(0.0284)	(0.0354)
Log likelihood	-67,937			

Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
The age covariate is $(x_k^{\text{last}}(t) - 65)/10$ where $x_k^{\text{last}}(t)$ represents the age last birthday. The time covariate t is $Time/10$, where $Time$ is determined by the calendar year (see Table 1).

Table 8. Trend model: estimated parameters with standard errors in parentheses.

Transition Type	$H \to F$	$F \to H$	$H \to D$	$F \to D$
$s =$	1	2	3	4
China (CLHLS)				
$\hat{\beta}_s$	-4.3794***	-1.6078***	-3.6880***	-2.1133***
	(0.0536)	(0.1156)	(0.0290)	(0.0555)
$\hat{\gamma}_s^{\text{age}}$	0.5810***	-0.2866***	0.7668***	0.4276***
	(0.0153)	(0.0345)	(0.0082)	(0.0159)
$\hat{\gamma}_s^{\text{female}}$	0.2105***	0.1167**	-0.2472***	-0.1645***
	(0.0313)	(0.0659)	(0.0157)	(0.0257)
$\hat{\gamma}_s^{\text{time}}$	-0.5349***	-0.7629***	-0.0053	-0.1511***
	(0.0371)	(0.0741)	(0.0188)	(0.0269)
Log likelihood	-84,334			
China (CLHLS) with residence				
$\hat{\beta}_s$	-4.5354***	-1.4714***	-3.6651***	-2.0858***
	(0.0563)	(0.1197)	(0.0300)	(0.0569)
$\hat{\gamma}_s^{\text{age}}$	0.5892***	-0.2953***	0.7657***	0.4261***
	(0.0154)	(0.0346)	(0.0082)	(0.0159)
$\hat{\gamma}_s^{\text{female}}$	0.2164***	0.1069*	-0.2484***	-0.1667***
	(0.0313)	(0.0659)	(0.0157)	(0.0258)
$\hat{\gamma}_s^{\text{urban}}$	0.2852***	-0.2482***	-0.0461***	-0.0492**
	(0.0296)	(0.0597)	(0.0159)	(0.0227)
$\hat{\gamma}_s^{\text{time}}$	-0.5160***	-0.7646***	-0.0082	-0.1511***
	(0.0373)	(0.0738)	(0.0188)	(0.0269)
Log likelihood	-84,272			
U.S. (HRS)				
$\hat{\beta}_s$	-4.0381***	-1.5513***	-4.5840***	-2.8933***
	(0.0319)	(0.0422)	(0.0381)	(0.0515)
$\hat{\gamma}_s^{\text{age}}$	0.6258***	-0.3857***	1.1422***	0.7062***
	(0.0130)	(0.0162)	(0.0155)	(0.0179)
$\hat{\gamma}_s^{\text{female}}$	0.2794***	0.0103	-0.4680***	-0.3733***
	(0.0262)	(0.0369)	(0.0284)	(0.0354)
$\hat{\gamma}_s^{\text{time}}$	-0.1519***	-0.2513***	-0.0865***	-0.0146
	(0.0282)	(0.0392)	(0.0317)	(0.0378)
Log likelihood	-67,899			

Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
The age covariate is $(x_k^{\text{last}}(t) - 65)/10$ where $x_k^{\text{last}}(t)$ represents the age last birthday. The time covariate t is $Time/10$, where $Time$ is determined by the calendar year (see Table 1).

Table 9. Frailty model: estimated parameters with standard errors in parentheses. The latent factor is assumed to follow a random walk process.

Transition Type	$H \to F$	$F \to H$	$H \to D$	$F \to D$
$s =$	1	2	3	4
China (CLHLS)				
$\hat{\beta}_s$	-4.2259***	-1.5543***	-3.6934***	-2.1004***
	(0.0537)	(0.1157)	(0.0298)	(0.0558)
$\hat{\gamma}_s^{\text{age}}$	0.5618***	-0.2944***	0.7670***	0.4273***
	(0.0156)	(0.0347)	(0.0082)	(0.0159)
$\hat{\gamma}_s^{\text{female}}$	0.2174***	0.1206**	-0.2473***	-0.1635***
	(0.0313)	(0.0658)	(0.0157)	(0.0257)
$\hat{\gamma}_s^{\text{time}}$	-0.7600***	-0.8442***	0.0019	-0.1737***
	(0.0360)	(0.0722)	(0.0211)	(0.0286)
$\hat{\alpha}_s$	0.2589***	0.1380***	-0.0055	0.0230**
	(0.0145)	(0.0276)	(0.0073)	(0.0105)
Log likelihood	-84,157			
China (CLHLS) with residence				
$\hat{\beta}_s$	-4.3921***	-1.4231***	-3.6709***	-2.0748***
	(0.0565)	(0.1199)	(0.0308)	(0.0571)
$\hat{\gamma}_s^{\text{age}}$	0.5713***	-0.3031***	0.7660***	0.4259***
	(0.0157)	(0.0348)	(0.0082)	(0.0159)
$\hat{\gamma}_s^{\text{female}}$	0.2242***	0.1112**	-0.2485***	-0.1656***
	(0.0313)	(0.0659)	(0.0157)	(0.0258)
$\hat{\gamma}_s^{\text{urban}}$	0.2998***	-0.2381***	-0.0465***	-0.0467**
	(0.0296)	(0.0597)	(0.0159)	(0.0227)
$\hat{\gamma}_s^{\text{time}}$	-0.7423***	-0.8443***	-0.0003	-0.1726***
	(0.0360)	(0.0721)	(0.0211)	(0.0286)
$\hat{\alpha}_s$	0.2622***	0.1343***	-0.0061	0.0219**
	(0.0144)	(0.0276)	(0.0073)	(0.0105)
Log likelihood	-84,092			
U.S. (HRS)				
$\hat{\beta}_s$	-3.9950***	-1.5583***	-4.5858***	-2.8888***
	(0.0325)	(0.0427)	(0.0385)	(0.0519)
$\hat{\gamma}_s^{\text{age}}$	0.6254***	-0.3857***	1.1422***	0.7062***
	(0.0130)	(0.0162)	(0.0155)	(0.0179)
$\hat{\gamma}_s^{\text{female}}$	0.2789***	0.0103	-0.4680***	-0.3732***
	(0.0262)	(0.0369)	(0.0284)	(0.0354)
$\hat{\gamma}_s^{\text{time}}$	-0.2120***	-0.2432***	-0.0842***	-0.0201
	(0.0298)	(0.0400)	(0.0324)	(0.0387)
$\hat{\alpha}_s$	-0.0641***	0.0122	0.0030	-0.0074
	(0.0088)	(0.0118)	(0.0090)	(0.0107)
Log likelihood	-67,877			

Note: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
The age covariate is $(x_k^{\text{last}}(t) - 65)/10$ where $x_k^{\text{last}}(t)$ represents the age last birthday. The time covariate t is $Time/10$, where $Time$ is determined by the calendar year (see Table 1).

6 Life Expectancy and Disability Prevalence: Comparison of China and the U.S.

We use micro-simulation, simulating the health states of 10,000 homogeneous individuals whose health state transition rates are assumed to be the estimated transition rates in the static, trend or frailty model. To generate random health states from the frailty model, we first simulate 1,000 frailty paths, then for each of the frailty paths, we simulate the health states of the 10,000 individuals. We demonstrate how to simulate the health states given the transition rates, and how to simulate the future lifetime given the health state paths in Appendix C.

For the trend and frailty models, we simulate health states for two cohorts, one starting in the year 1998 at age 65 and the other starting in 2014 at age 65. We select these two years because the data used for estimation started in 1998 and ended in 2014. For the simulated cohort aged 65 in 1998 we set the time equal to 1 in the transition model; for the simulated cohort aged 65 in 2014 we set the time equal to 17. As a result, the transition rates for the simulated cohort aged 65 in 2014 include the impact of trend between 1998 and 2014, whereas the transition rates for the simulated cohort aged 65 in 1998 do not. At the same age, these two cohorts have similar levels of mortality rates, whereas the disability and recovery rates vary significantly due to the stronger time trends associated with the two transitions. The detailed results can be found in Appendix D.1.

6.1 Survival curves

Figures 11 and 12 compare the Chinese and U.S. survival curves, based on our model and the estimated transitions for a cohort of individuals who were healthy at 65. These survival curves allow for disability transitions and differences in disabled and healthy mortality rates. The survival curve of the trend model cannot be visually separated from the sample mean of the simulated survival curves from the frailty model, so the former is omitted from the figure. As expected, controlling for gender and time effects, the survival curve of the U.S. is above that of China at almost all ages. The elderly in the U.S. live longer on average than their counterparts in China. The impact of improvement over the sample period can also be discerned when comparing the survival curve of the static model with that of the trend model in both China and the U.S. Figure 12 shows that for the simulated cohort aged 65 in 2014, the survival curve of the static model is the lowest among the three models at all ages. As a result, assuming a static model without time trends will underestimate life expectancy and the underestimation is more severe for younger cohorts.

We also plot survival curves for the 75-year-old in Appendix D.2. Similar conclusions are drawn, except that these curves show a faster decrease with age and therefore have a less rectangular shape than the curves for the 65-year-old.

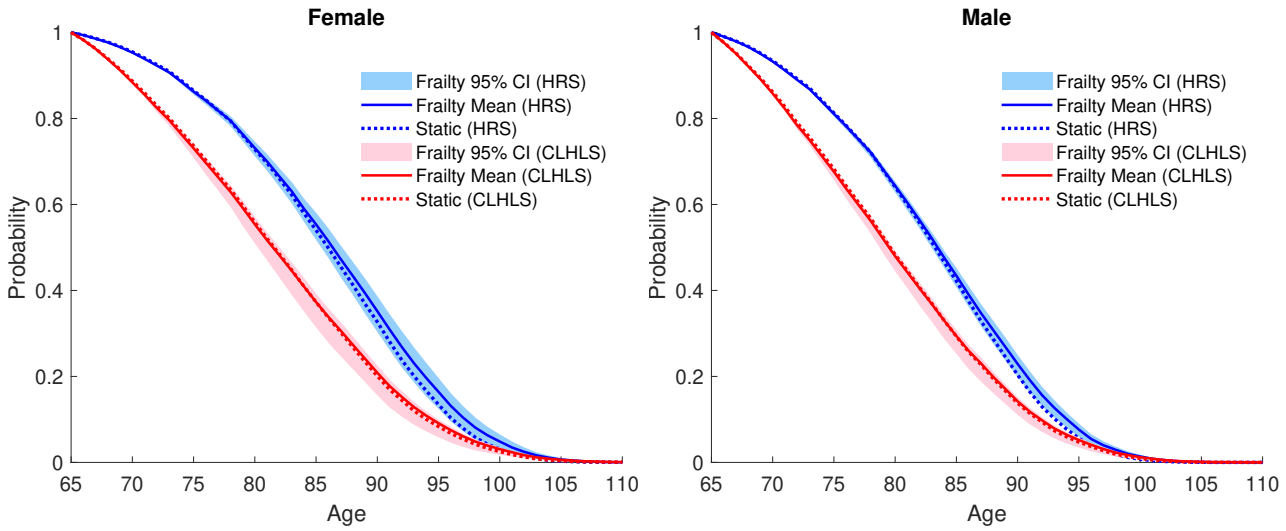

Figure 11. Survival curves of the static and frailty models for a cohort of individuals who were healthy at age 65 in the year 1998. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

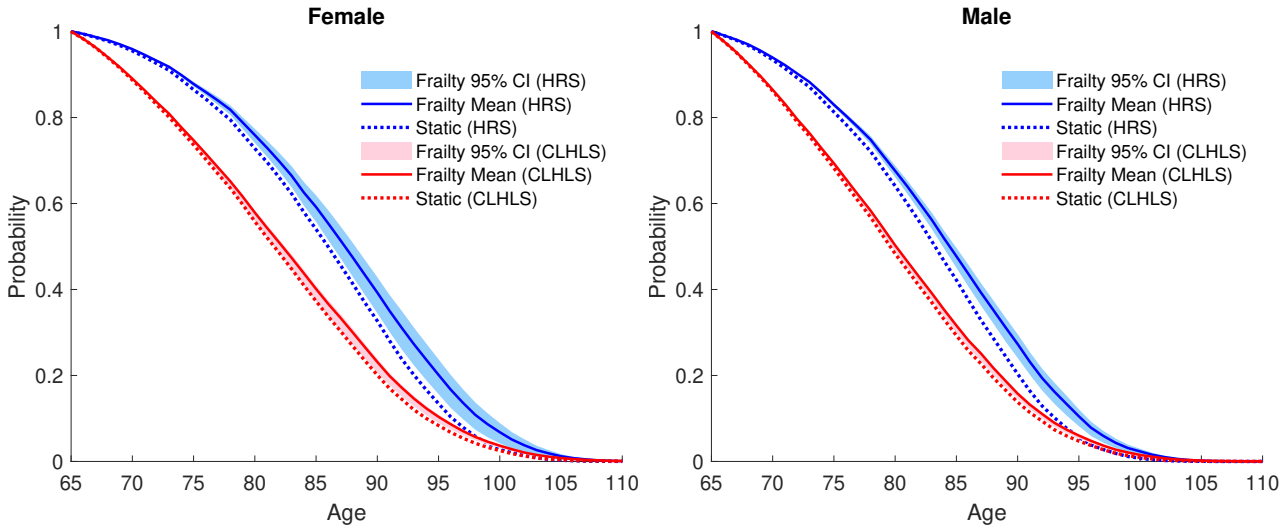

Figure 12. Survival curves of the static and frailty models for a cohort of individuals who were healthy at age 65 in the year 2014. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

Table 10 shows estimates of life expectancy, healthy life expectancy, disabled life expectancy, the proportion of life expectancy spent in the healthy state (i.e. without functional disability) and the average age at the onset of disability, simulated from the static model. We show the estimates for the 65-year-old and 75-year-old healthy individuals by gender and nation. The gap in total life expectancy between China and the U.S. is about 3.6 years for healthy females at 65 and 2.8 years for healthy males at 65. Interestingly, the model estimates that the average age at onset of disability is very similar for Chinese and U.S. males or females. Although Chinese healthy mortality is higher, the disability rates and disabled mortality compensate to produce similar expected ages for the onset of functional disability. Even more striking is that the Chinese elderly are expected to spend more time, as a proportion of their total future lifetime, in the healthy state without functional disability. So although Chinese life expectancy is lower than that of the U.S. for both women and men, the CLHLS data suggests that seniors in China are likely to spend a greater proportion of their time free of functional disability than their U.S. counterparts.

Table 10. Static model: future lifetime statistics for 65- and 75-year-old healthy individuals, including mean, standard error of the mean in brackets, and standard deviation (Std). The maximum attainable age is 110.

	Healthy at 65				Healthy at 75			
	CLHLS		HRS		CLHLS		HRS	
	Female	Male	Female	Male	Female	Male	Female	Male
Total future lifetime								
Mean	16.82	15.04	20.41	17.87	10.96	9.63	13.06	10.93
	(0.09)	(0.09)	(0.09)	(0.08)	(0.07)	(0.06)	(0.07)	(0.06)
Std	9.13	8.54	8.53	7.97	6.90	6.34	6.62	6.00
Healthy future lifetime								
Mean	15.63	14.26	17.24	16.11	10.00	9.01	10.57	9.60
	(0.09)	(0.08)	(0.08)	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)
Std	8.83	8.36	8.07	7.74	6.58	6.13	6.14	5.76
Disabled future lifetime								
Mean	1.18	0.78	3.17	1.76	0.95	0.63	2.49	1.33
	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)
Std	2.75	2.16	4.40	3.13	2.34	1.86	3.68	2.56
Healthy future lifetime over total future lifetime								
Mean	0.934	0.952	0.853	0.905	0.924	0.944	0.824	0.887
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Std	0.153	0.135	0.198	0.169	0.178	0.159	0.243	0.211
Age at onset of disability conditional on becoming disabled								
Mean	79.55	78.65	79.71	78.90	85.03	84.14	84.61	83.86
	(0.17)	(0.19)	(0.11)	(0.12)	(0.13)	(0.14)	(0.08)	(0.09)
Std	8.49	8.09	8.08	7.51	6.34	5.87	5.84	5.36

Table 11 shows the same simulated future lifetime statistics for the trend model with starting years of 1998 and 2014. For the simulated cohort aged 65 in 1998, the expected ratio of healthy future lifetime over total future lifetime is similar to that estimated with the static model. There are some increases in life expectancy for the trend model compared with the static model for the 1998 starting year, although these are not major. The increases in total life expectancy range from one month to less than five months among the 65-year-old. For the simulated cohort aged 65 in 2014, compared to the one aged 65 in 2014, we see increases in both life expectancy and healthy life expectancy in China and the U.S. for both males and females. The increases provide an indication of the impact of trends between 1998 and 2014 on life expectancy and healthy life expectancy. The proportion of future healthy life expectancy increases in China and the U.S. for both males and females. The model estimates morbidity compression based on functional disability when time trends are included in the transition model.

The simulated life expectancy results using the frailty model are comparable to those of the trend model, as expected, since the impact of the frailty factor, which follows a random walk process, is averaged out when calculating the expectation. The frailty model allows us to construct confidence interval of the mean and to measure the significance of time trend on life expectancy. We find that, for the simulated cohort aged 65 or 75 in 2014, regardless of gender or nation, the lower endpoint of the 95% confidence interval of total life expectancy exceeds the corresponding total life expectancy estimated with the static model. By contrast, the total life expectancy estimated with the trend model lies within the interval of the frailty model. Disregarding the time trend, therefore, significantly underestimates the total life expectancy for the younger cohort. The detailed results can be found in Appendix D.2.

Table 11. Trend model: future lifetime statistics for 65- and 75-year-old healthy individuals in 1998 and 2014, including mean, standard error of the mean in brackets, and standard deviation (Std). The maximum attainable age is 110.

	Healthy at 65				Healthy at 75			
	CLHLS		HRS		CLHLS		HRS	
	Female	Male	Female	Male	Female	Male	Female	Male
1998								
Total future lifetime								
Mean	17.04	15.13	20.80	18.19	10.99	9.62	13.12	10.91
	(0.09)	(0.09)	(0.09)	(0.08)	(0.07)	(0.06)	(0.07)	(0.06)
Std	9.44	8.76	8.87	8.30	7.06	6.43	6.79	6.15
Healthy future lifetime								
Mean	15.90	14.34	17.62	16.43	9.99	8.97	10.58	9.56
	(0.09)	(0.09)	(0.09)	(0.08)	(0.07)	(0.06)	(0.06)	(0.06)
Std	9.33	8.67	8.58	8.18	6.84	6.28	6.37	5.92
Disabled future lifetime								
Mean	1.14	0.79	3.18	1.76	1.00	0.65	2.53	1.36
	(0.03)	(0.02)	(0.05)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)
Std	3.09	2.47	4.52	3.21	2.55	1.97	3.75	2.62
Healthy future lifetime over total future lifetime								
Mean	0.935	0.949	0.853	0.905	0.916	0.939	0.820	0.884
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Std	0.164	0.149	0.202	0.173	0.195	0.172	0.247	0.215
Age at onset of disability conditional on becoming disabled								
Mean	76.69	75.77	79.69	78.73	83.34	82.62	84.35	83.66
	(0.17)	(0.18)	(0.11)	(0.13)	(0.12)	(0.13)	(0.08)	(0.09)
Std	7.72	7.21	8.44	7.85	5.81	5.24	5.90	5.44
2014								
Total future lifetime								
Mean	17.59	15.65	21.79	19.11	11.52	9.97	13.88	11.68
	(0.10)	(0.09)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.06)
Std	9.59	8.92	9.10	8.55	7.34	6.58	7.06	6.41
Healthy future lifetime								
Mean	16.82	15.10	18.74	17.45	10.84	9.56	11.47	10.41
	(0.10)	(0.09)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.06)
Std	9.58	8.90	9.17	8.61	7.18	6.52	6.83	6.32
Disabled future lifetime								
Mean	0.78	0.55	3.06	1.66	0.69	0.41	2.41	1.27
	(0.03)	(0.03)	(0.05)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)
Std	3.10	2.54	4.63	3.24	2.52	1.83	3.80	2.62
Healthy future lifetime over total future lifetime								
Mean	0.959	0.968	0.860	0.911	0.950	0.966	0.834	0.894
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Std	0.147	0.131	0.207	0.174	0.163	0.140	0.244	0.210
Age at onset of disability conditional on becoming disabled								
Mean	77.34	75.82	80.95	79.74	84.11	82.93	85.36	84.49
	(0.24)	(0.26)	(0.13)	(0.14)	(0.18)	(0.20)	(0.09)	(0.11)
Std	7.82	7.17	8.98	8.25	6.19	5.57	6.39	5.90

6.2 Health distribution

We have so far shown estimates from the model transitions for life expectancy, including disabled life expectancy which reflects how long on average an individual would need long-term care based on functional disability. We can also use the transition model to estimate the proportion of disabled elderly for a cohort of individuals as they age. This provides a more informative picture of functional disability than just an average time spent disabled or an average age of onset of disability.

Figure 13 shows the simulated proportion of older adults in the disabled state for a cohort of healthy individuals who were 65 years old in the year 1998. The estimates given by the trend and static models are within the 95% confidence intervals of those given by the frailty model. The probability of being disabled increases initially with age since at younger ages, for healthy individuals, the chance of disability is greater than the chance of death. At more advanced ages, the healthy mortality rate exceeds the disability rate, so the proportion of disabled elderly declines.

Controlling for age and gender, the model simulations show that the estimated transition rates imply a higher chance of being disabled for the elderly in the U.S. than those in China. Based on the frailty process, the 95% confidence interval for the U.S. is more or less symmetric around the mean, while that for China is skewed to higher proportions. Long-term care benefit payouts in China would be expected to have a heavier right tail, with larger-than-expected payments more likely to occur compared with the U.S.

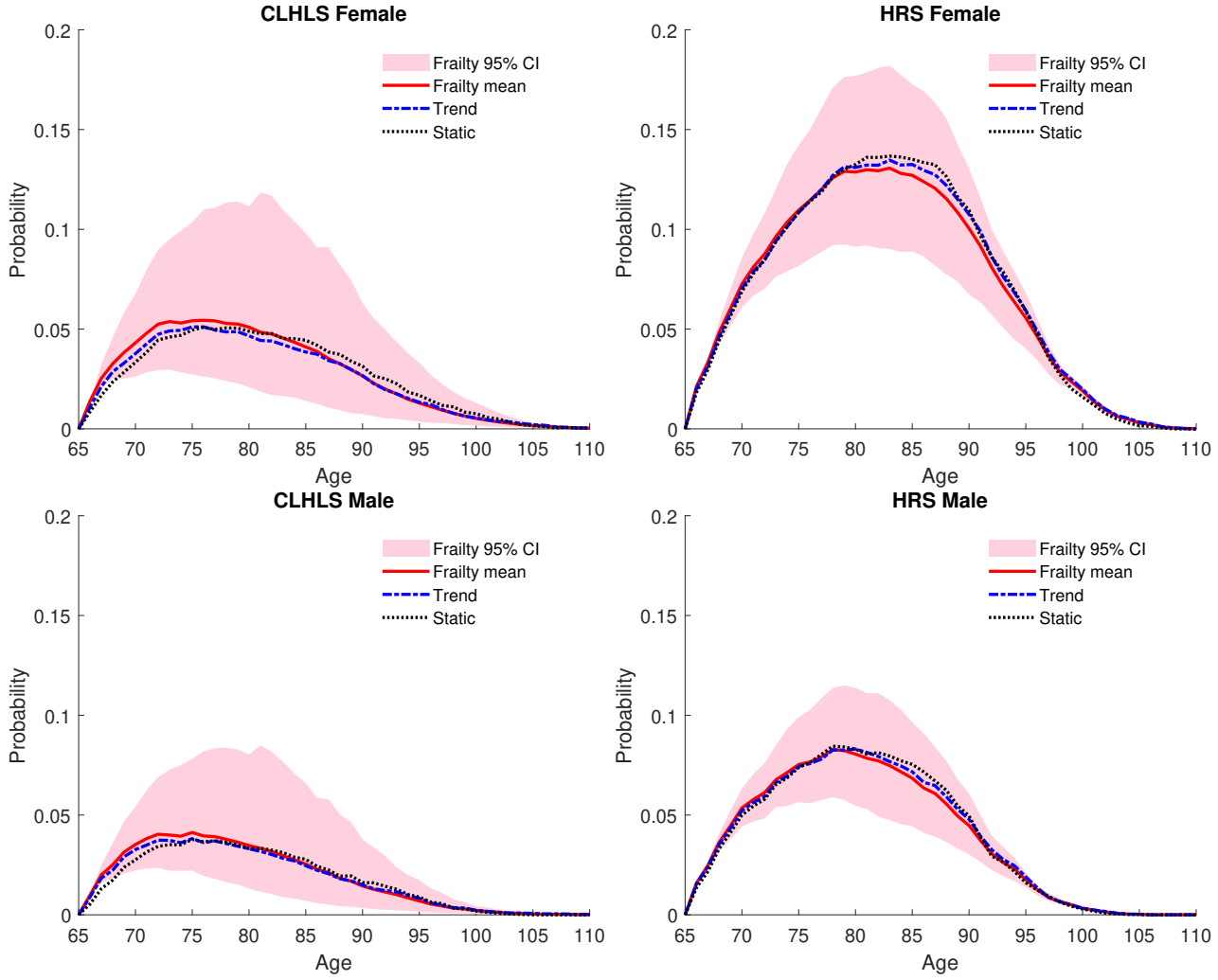

Figure 13. Probability of being in the disabled state for a cohort of individuals who were healthy at age 65 in the year 1998. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.

Figure 14 shows the probability of being disabled for a cohort of healthy individuals who were 65 years old in the year 2014. In both China and the U.S. the trend model produces lower probabilities at all ages than those of the static model. The gaps tend to be larger when the probabilities are higher. Ignoring the time trend (i.e. the static curve) overestimates the probability of being disabled by a noticeable margin. For pricing long-term care insurance, it is critical to include time trend in the transition model to ensure actuarial premiums reflect expected trends. Our model allows these effects to be readily captured.

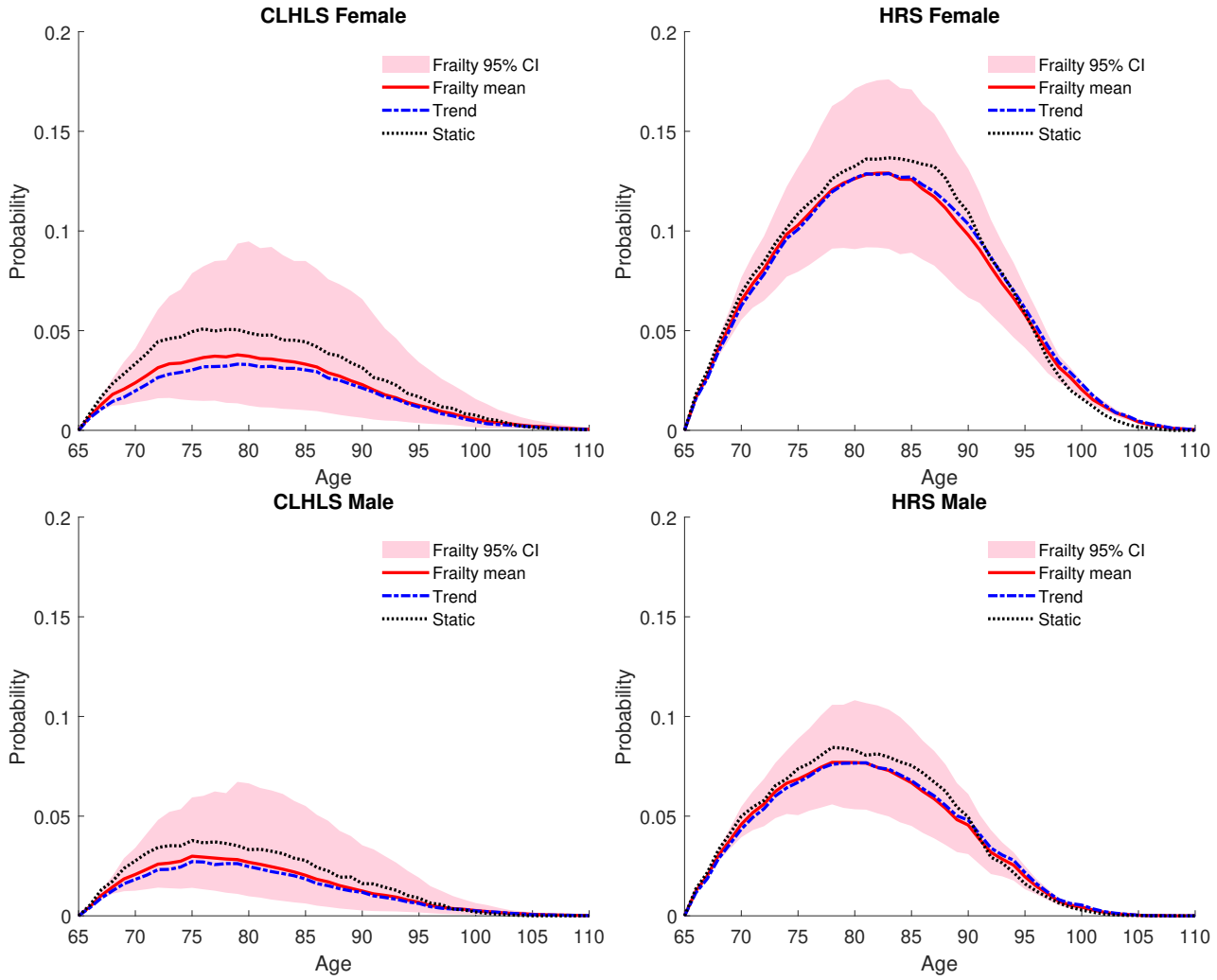

Figure 14. Probability of being in the disabled state for a cohort of individuals who were healthy at age 65 in the year 2014. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.

Similar conclusions can be drawn from the probabilities of being disabled for a cohort of healthy individuals who were 75 in 1998 and 2014. The plots are displayed in Appendix D.3.

6.3 Urban-rural differences in China

China has a unique urban-rural dual system that gives rise to social and economic inequality between the urban and rural populations (Chan and Wei, 2019). The socioeconomic differences, along with the disparity in the health care system (Hougaard et al., 2011) and long-term care expenditures (Li et al., 2013), have consequences for the elderly life expectancy and health distribution.

Figure 15 uses our estimated model for China to compare the survival curves for urban and rural residents who were healthy at age 65 in the year 1998. The urban-rural difference in the survival curves is small. A noticeable difference between the two panels in Figure 15 is the wider confidence intervals for urban residents, suggesting greater health inequity within the urban population, similar to the results in Yang and Kanavos (2012) who show that the urban population is more prone to income-related health inequalities than their rural counterparts.

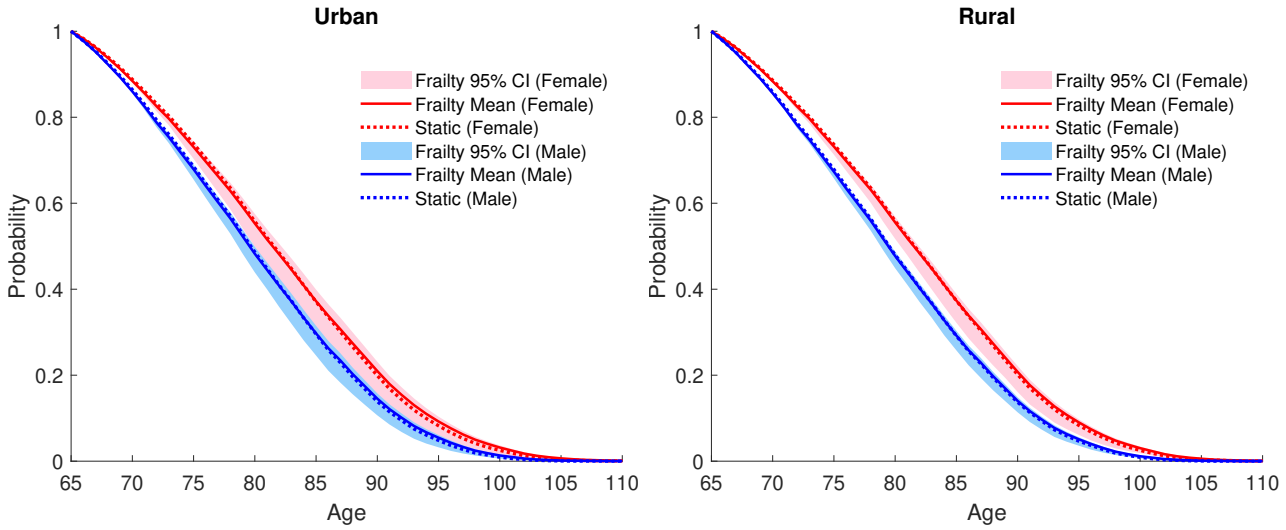

Figure 15. Survival curves of the static and frailty models (with the residence covariate) for a cohort of individuals who were healthy at age 65 in the year 1998. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

Figure 16 gives the survival curve of Chinese who were healthy at 65 in the year 2014. Compared to Figure 15, the confidence intervals of all the sub-populations are narrower in Figure 16, and the lower bound of the confidence interval is closer to the mean. These changes result from the strong mortality improvement for the disabled population in China that increases the survival probability. The lower bound is affected more than the upper bound because for those living longer there is a higher-than-average risk of disability as shown in Figure 14.

The survival curves for the 75-year-old Chinese show similar patterns in terms of urban-rural and cohort differences. They are shown in Appendix D.2.

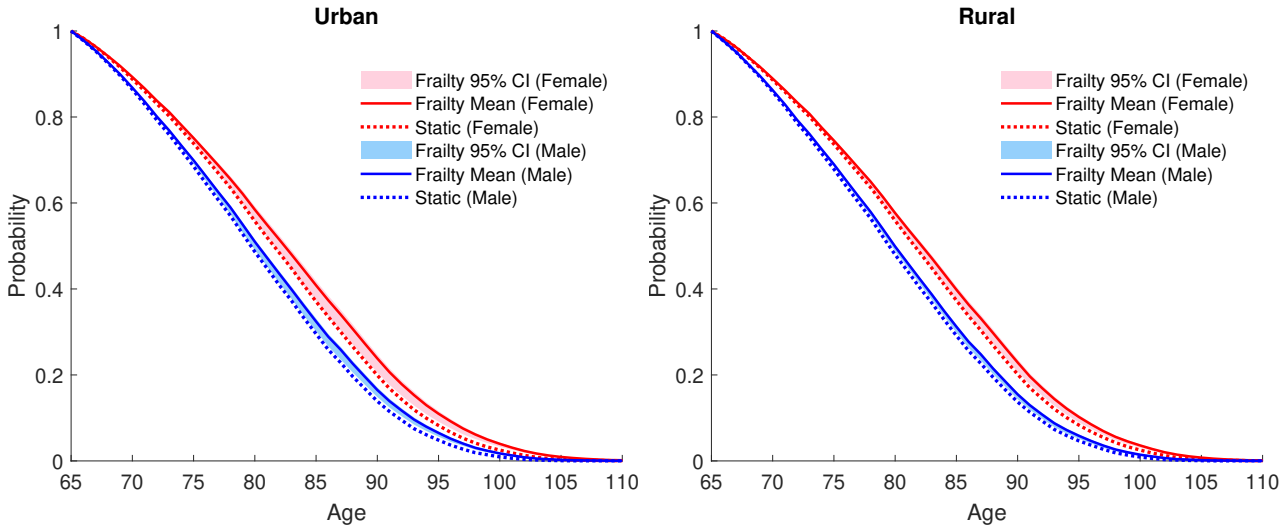

Figure 16. Survival curves of the static and frailty models (with the residence covariate) for a cohort of individuals who were healthy at age 65 in the year 2014. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

Table 12 shows the simulated life expectancy using the static model for the Chinese urban and rural residents. Urban residents generally have a longer total life expectancy, but they tend to spend fewer years in the healthy state and to become disabled at slightly younger ages. The urban residents have lower mortality as estimated in the transition model. This may also reflect that urban residents have better access to health care services that can improve life expectancy (Hao et al., 2020). An interesting result, based on the CLHLS data and our transition model, is that urban residents are more likely to become disabled and less likely to recover from disability than their rural counterparts, which shortens their healthy life expectancy. These results are consistent with prior studies that find a significant association between rural residency and fewer ADL disabilities (see e.g. Zeng and Vaupel, 2002; Zeng et al., 2010; Zimmer et al., 2010). Poorer environment quality (e.g. air and water pollution) and more sedentary lifestyle are possible factors that contribute to a higher disability rate among urban Chinese residents (Gong et al., 2012).

Table 12. Static model with residence: future lifetime statistics for 65- and 75-year-old healthy individuals, including mean, standard error of the mean in brackets, and standard deviation (Std). The maximum attainable age is 110.

	Healthy at 65				Healthy at 75			
	Urban		Rural		Urban		Rural	
	Female	Male	Female	Male	Female	Male	Female	Male
Total future lifetime								
Mean	16.81	15.11	16.82	14.98	10.99	9.69	10.94	9.58
	(0.09)	(0.09)	(0.09)	(0.09)	(0.07)	(0.06)	(0.07)	(0.06)
Std	9.10	8.53	9.15	8.55	6.89	6.34	6.90	6.34
Healthy future lifetime								
Mean	15.35	14.14	15.80	14.34	9.83	8.93	10.11	9.05
	(0.09)	(0.08)	(0.09)	(0.08)	(0.07)	(0.06)	(0.07)	(0.06)
Std	8.74	8.31	8.87	8.38	6.51	6.09	6.62	6.15
Disabled future lifetime								
Mean	1.46	0.97	1.02	0.64	1.16	0.76	0.83	0.53
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Std	3.09	2.43	2.53	1.91	2.60	2.05	2.16	1.68
Healthy future lifetime over total future lifetime								
Mean	0.919	0.940	0.943	0.960	0.908	0.932	0.934	0.952
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Std	0.170	0.150	0.142	0.122	0.195	0.174	0.167	0.147
Age at onset of disability conditional on becoming disabled								
Mean	79.47	78.54	79.78	78.94	84.89	84.10	85.14	84.39
	(0.15)	(0.17)	(0.18)	(0.20)	(0.12)	(0.13)	(0.14)	(0.15)
Std	8.41	8.08	8.62	8.21	6.24	5.90	6.36	5.95

Table 13 shows the simulated future lifetime statistics using the trend model with residence. The urban-rural gap in total life expectancy widened between 1998 and 2014, increasing from 0.05 years to just below 0.4 years for healthy females at 65, and increasing from less than 0.2 years to more than 0.3 years for healthy males at 65. Both urban and rural residents enjoyed longer healthy life expectancy, and the gains were greater for urban residents. In 1998, the healthy life expectancy was lower for urban residents in both gender and age groups. The gap was closed, and in 2014, urban residents were expected to have a longer healthy life expectancy. Over the course of the data period, the average onset of disability conditional on being disabled was delayed by almost 1.1 years for 65-year-old healthy urban females while that for their rural counterparts was about 0.5 years. Including the time trend highlights a growing urban-rural disparity in longevity and health. The simulation results of the frailty model are similar to those of the trend model shown in Table 13 since the randomness of the frailty factor is averaged out across the simulations. They can be found in Appendix D.2.

Table 13. Trend model with residence: future lifetime statistics for 65- and 75-year-old healthy individuals in 1998 and 2014, including mean, standard error of the mean in brackets, and standard deviation (Std). The maximum attainable age is 110.

	Healthy at 65				Healthy at 75			
	Urban		Rural		Urban		Rural	
	Female	Male	Female	Male	Female	Male	Female	Male
1998								
Total future lifetime								
Mean	17.06	15.26	17.01	15.07	11.03	9.67	10.98	9.56
	(0.09)	(0.09)	(0.09)	(0.09)	(0.07)	(0.06)	(0.07)	(0.06)
Std	9.47	8.82	9.42	8.76	7.11	6.45	7.07	6.42
Healthy future lifetime								
Mean	15.65	14.32	16.03	14.41	9.82	8.90	10.11	9.02
	(0.09)	(0.09)	(0.09)	(0.09)	(0.07)	(0.06)	(0.07)	(0.06)
Std	9.34	8.71	9.31	8.66	6.81	6.29	6.86	6.29
Disabled future lifetime								
Mean	1.40	0.95	0.98	0.66	1.21	0.77	0.86	0.54
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Std	3.49	2.76	2.80	2.21	2.84	2.17	2.36	1.78
Healthy future lifetime over total future lifetime								
Mean	0.920	0.939	0.944	0.957	0.900	0.927	0.928	0.948
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Std	0.183	0.162	0.151	0.135	0.211	0.187	0.180	0.157
Age at onset of disability conditional on becoming disabled								
Mean	76.75	75.75	76.95	76.11	83.42	82.63	83.48	82.75
	(0.16)	(0.17)	(0.18)	(0.20)	(0.11)	(0.12)	(0.13)	(0.14)
Std	7.86	7.17	7.83	7.39	5.90	5.34	5.86	5.27
2014								
Total future lifetime								
Mean	17.85	15.87	17.54	15.55	11.66	10.14	11.46	9.90
	(0.10)	(0.09)	(0.10)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)
Std	9.72	9.04	9.60	8.91	7.43	6.67	7.31	6.56
Healthy future lifetime								
Mean	16.86	15.18	16.84	15.08	10.85	9.62	10.86	9.54
	(0.10)	(0.09)	(0.10)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)
Std	9.66	8.99	9.57	8.88	7.25	6.58	7.17	6.50
Disabled future lifetime								
Mean	0.99	0.69	0.69	0.48	0.81	0.52	0.61	0.35
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
Std	3.49	2.85	2.91	2.32	2.74	2.08	2.36	1.72
Healthy future lifetime over total future lifetime								
Mean	0.949	0.961	0.964	0.972	0.941	0.957	0.955	0.970
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Std	0.161	0.145	0.138	0.121	0.177	0.156	0.155	0.131
Age at onset of disability conditional on becoming disabled								
Mean	77.84	76.19	77.47	76.18	84.06	83.10	84.11	82.78
	(0.23)	(0.24)	(0.25)	(0.27)	(0.17)	(0.18)	(0.19)	(0.20)
Std	8.27	7.46	7.78	7.26	6.24	5.72	6.17	5.31

Figure 17 compares the probability of being disabled by gender and residence for a cohort of healthy individuals who were 65 years old in 1998. Controlling for age and gender, a higher proportion of urban residents are expected to be functionally disabled than their rural counterparts. Urban residents are more likely to become disabled, less likely to recover, and have lower mortality rates. Figure 13 shows that the Chinese population is subject to a higher degree of uncertainty in their disability risk. Decomposing the Chinese population into urban and rural residents reveals that urban residents account for this greater uncertainty, supporting the conclusion that health disparity is larger within the Chinese urban population.

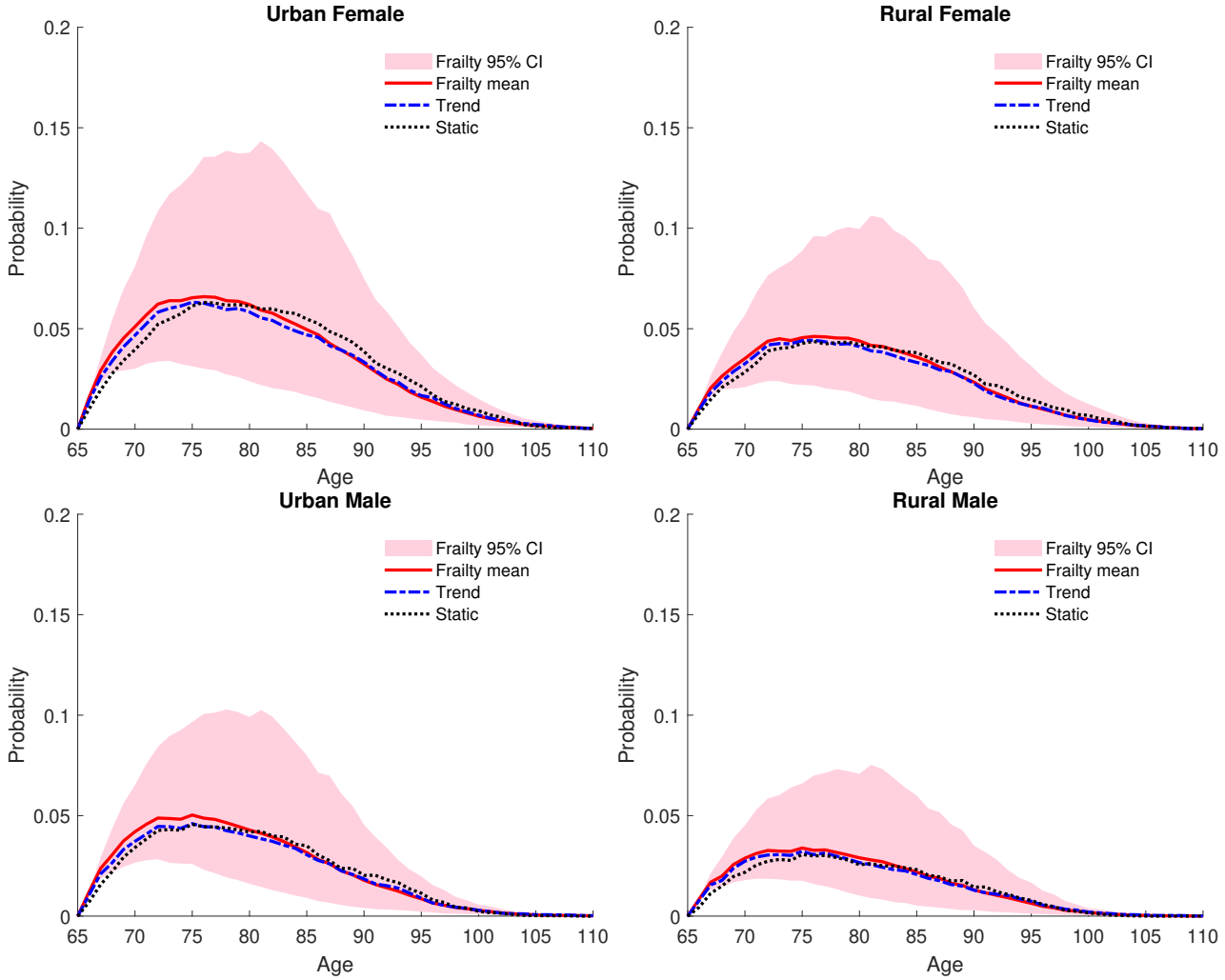

Figure 17. Probability of being in the disabled state for a cohort of individuals who were healthy at age 65 in the year 1998. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.

Figure 18 shows the probabilities of being in the disabled state for the simulated cohort aged 65 and healthy in 2014. Using the static model consistently overestimates the probability of being disabled for both urban and rural residents. The degree of overestimation varies with gender and residence, but is most severe for urban females.

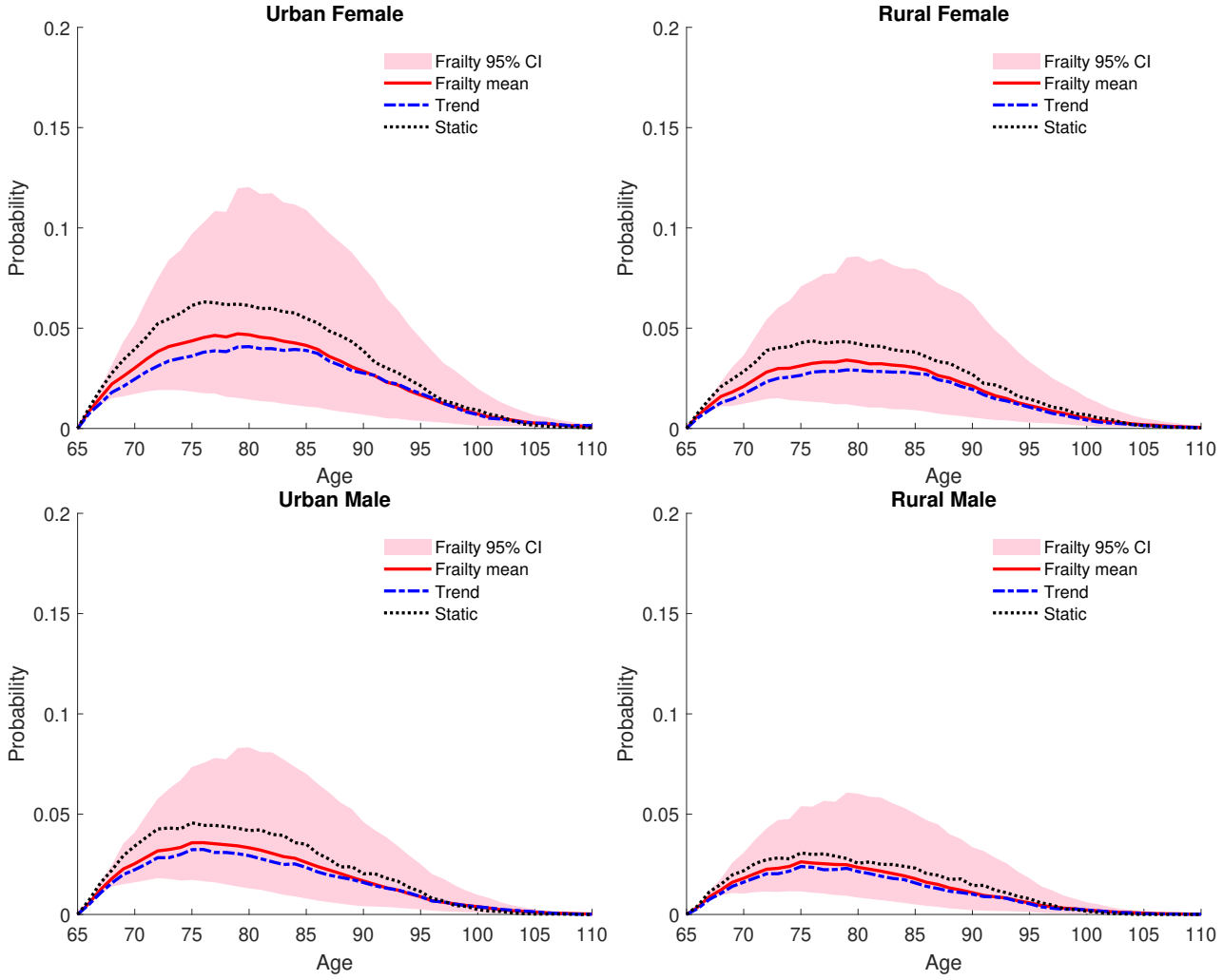

Figure 18. Probability of being in the disabled state for a cohort of individuals who were healthy at age 65 in the year 2014. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.

We plot the same curves for the 75-year-old showing urban residents continue to experience higher probabilities with greater uncertainty of being disabled. The figures are shown in Appendix D.3.

7 Conclusions

Declining family support and a growing need for private long-term care in China mean that the elderly Chinese will face long-term care financing issues, similar to their U.S. peers. Since the demand for long-term care is largely driven by health status, in particular functional disability, a comparison of the functional disability and mortality experience between China and the U.S. is critical in informing the development of the long-term care system in China. At the same time, understanding the driving factors for mortality and functional disability in both the U.S. and China is important. We develop, apply and estimate transition models based on Li et al. (2017) and Sherris and Wei (2021) to capture time trends and systematic uncertainty in health transitions among the Chinese elderly and compare the differences with the U.S. using individual-level longitudinal survey data.

Based on the data between 1998 and 2014, we confirm how the elderly in the U.S. have a longer life expectancy compared to their Chinese counterparts. The Chinese transition data indicates a smaller proportion of future lifetime will be spent functionally disabled. By including time trends our model shows morbidity compression in both the U.S. and China. Although the elderly Chinese are forecast to have lower probabilities of being disabled than the U.S. elderly, they are estimated to have a higher level of variability in the probability of being functionally disabled.

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Supplementary Material

A Supplementary Exploratory Data Analysis Results

A.1 Crude transition rates by time

Figure A.1 and Figure A.2 show the crude transition rates by time. We are motivated by the autoregressive features in the crude rates to model the frailty factor as an AR(1) process.

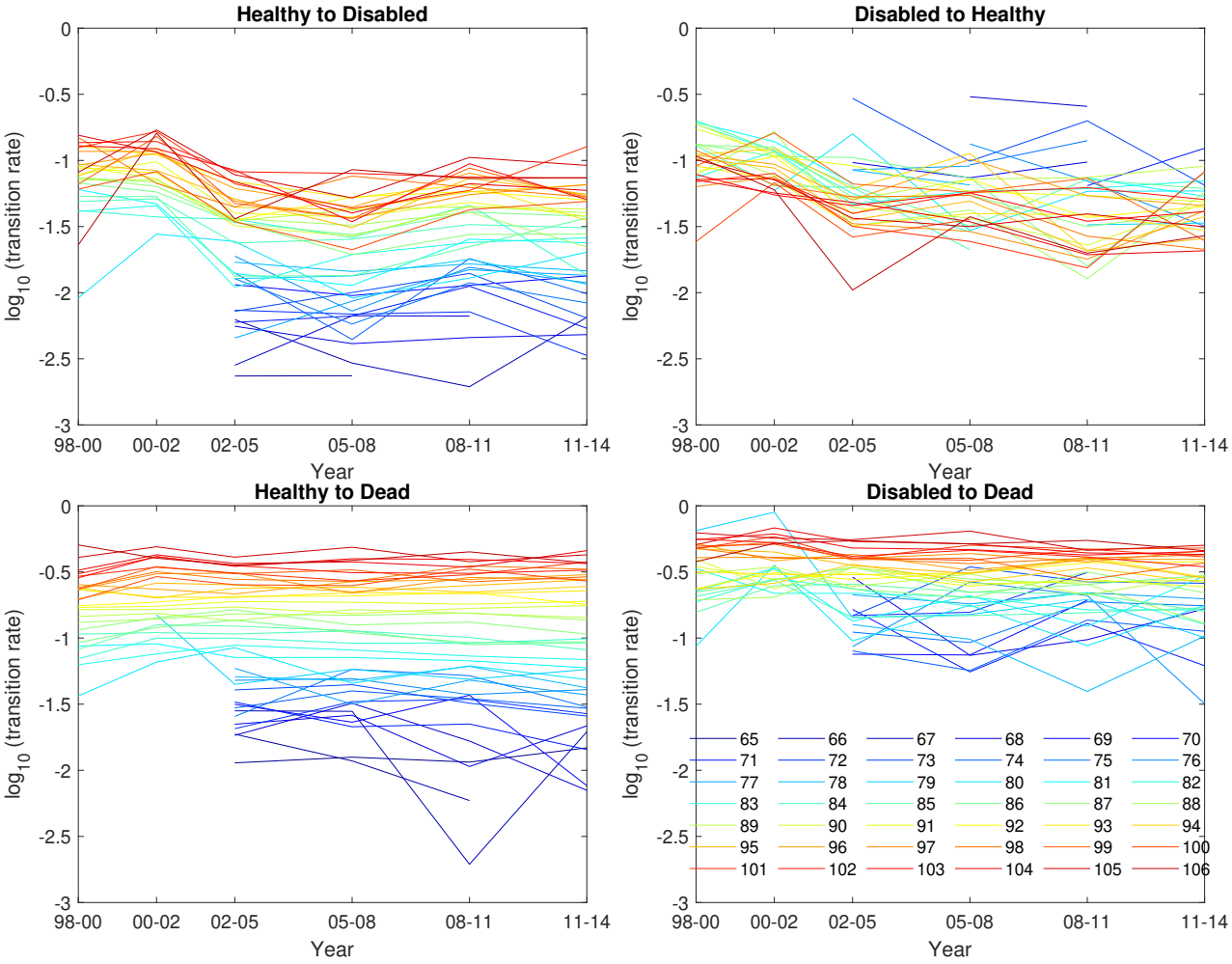

Figure A.1. Crude health transition rates for both genders based on the selected CLHLS sample.

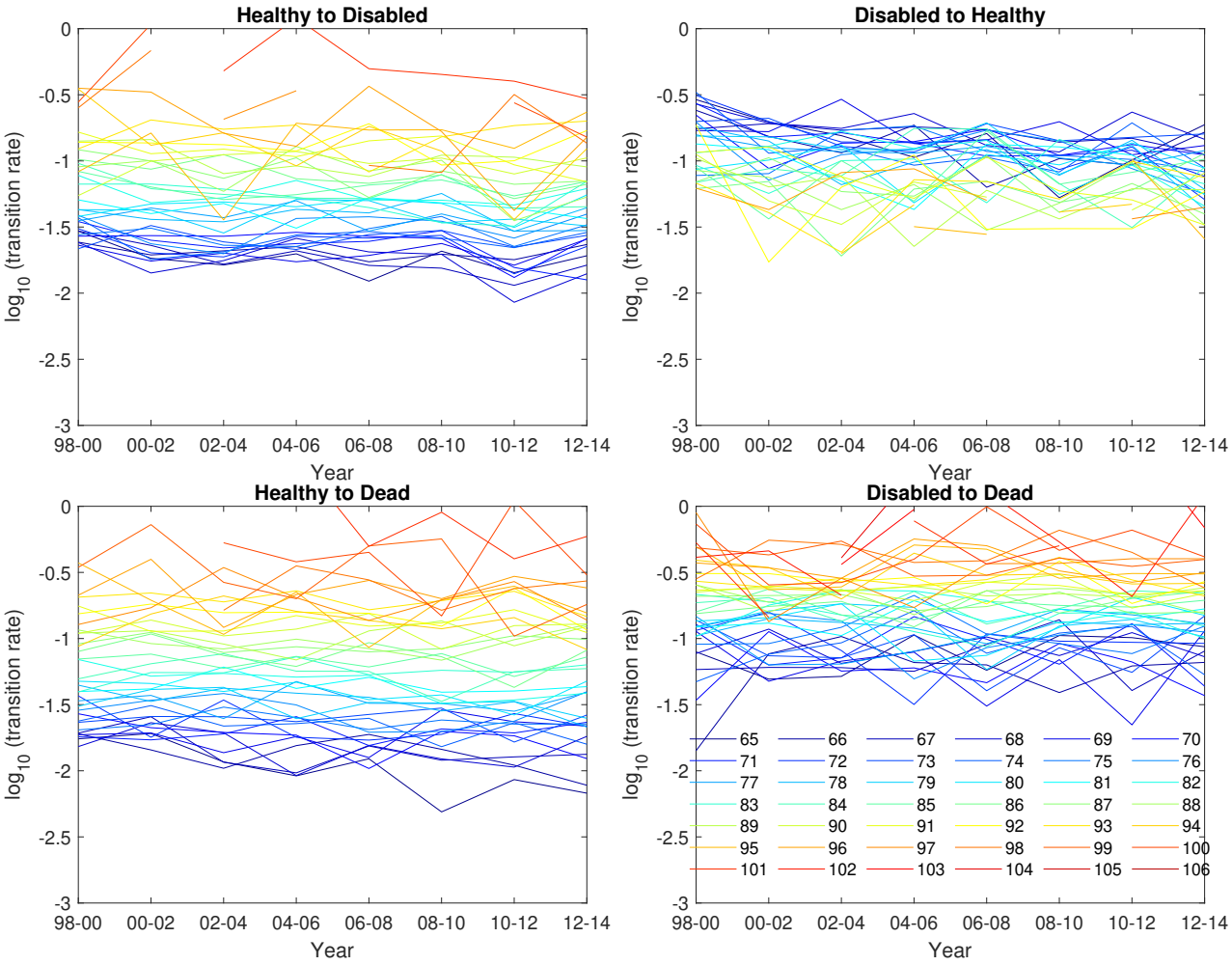

Figure A.2. Crude health transition rates for both genders based on the selected HRS sample.

A.2 Delay in death reporting

Table A.1 displays the number of deaths reported in each wave based on the full CLHLS sample between 1998 to 2014, i.e. before any data cleaning. We can see that most of the deaths occurred in the second half of a survey year were reported in the next interview wave. Table A.2 shows that the delay in death reporting also exists in the HRS data.

Table A.1. The number of deaths reported in each wave of the full CLHLS sample.

Year of death	Month of death											
	1	2	3	4	5	6	7	8	9	10	11	12
Wave 2 (survey year 2000)												
1998	0	0	0	15	62	83	101	130	84	109	115	124
1999	179	147	154	143	121	123	145	122	147	163	147	188
2000	153	169	145	87	82	61	38	6	1	3	2	2
Wave 3 (survey year 2002)												
2000	0	0	0	0	0	2	43	120	110	140	139	147
2001	166	178	204	150	144	112	143	144	149	185	197	256
2002	173	181	124	85	43	7	1	0	0	0	0	0
Wave 4 (survey year 2005)												
2002	0	0	2	19	42	99	85	100	81	114	115	157
2003	184	170	158	197	155	161	183	197	145	228	211	257
2004	197	215	221	163	155	125	154	142	125	198	165	216
2005	182	187	136	83	29	9	1	2	2	0	3	2
Wave 5 (survey year 2008-09)												
2005	7	1	14	23	48	63	67	76	58	90	103	151
2006	127	131	169	122	173	158	177	175	133	212	180	195
2007	124	129	157	128	134	143	136	170	131	183	168	207
2008	154	153	143	100	86	66	27	17	3	4	2	5
Wave 6 (survey year 2011-12)												
2008	0	0	2	3	2	19	61	106	143	109	134	172
2009	186	182	143	113	121	124	143	160	134	181	193	221
2010	204	168	169	151	144	115	141	140	132	148	159	167
2011	188	177	158	102	100	84	81	50	27	23	22	35
2012	23	15	24	21	8	8	2	2	1	0	0	1
Wave 7 (survey year 2014)												
2011	6	4	3	2	4	7	9	18	41	34	44	74
2012	103	109	92	60	56	79	83	68	59	91	96	129
2013	118	104	88	81	64	82	61	62	64	94	86	105
2014	110	108	74	64	43	16	15	7	4	3	2	4

Table A.2. The number of deaths reported in each wave of the HRS.

Year of death	Month of death											
	1	2	3	4	5	6	7	8	9	10	11	12
Wave 4 (survey year 1998)												
1995	1	1	2	0	0	0	2	0	3	2	2	13
1996	14	30	26	39	28	38	33	27	30	33	35	45
1997	50	49	45	53	47	44	54	37	27	49	39	36
1998	39	53	40	20	21	8	11	8	6	4	3	5
Wave 5 (survey year 2000)												
1998	0	2	10	12	23	27	31	33	38	44	40	42
1999	58	45	56	52	58	54	57	56	66	53	56	62
2000	57	48	49	28	22	14	10	9	5	2	0	1
Wave 6 (survey year 2002)												
2000	1	1	6	11	15	20	18	33	34	51	37	47
2001	55	43	47	49	39	57	68	73	62	81	62	66
2002	51	44	58	41	51	27	28	27	13	12	11	4
Wave 7 (survey year 2004)												
2002	1	1	0	0	4	10	20	28	20	31	42	44
2003	46	50	57	46	58	55	62	51	45	45	53	68
2004	52	60	55	46	41	27	25	8	12	7	5	0
Wave 8 (survey year 2006)												
2004	0	1	1	9	8	19	31	28	39	32	48	40
2005	46	43	67	44	45	37	45	58	58	51	67	64
2006	60	47	56	32	36	22	31	14	13	11	7	10
Wave 9 (survey year 2008)												
2006	0	0	1	8	6	16	32	22	38	36	43	42
2007	39	47	35	43	57	42	50	47	43	61	50	57
2008	54	63	56	53	29	28	28	13	14	11	6	1
Wave 10 (survey year 2010)												
2008	1	3	3	5	9	19	34	28	22	30	40	43
2009	38	38	45	48	45	46	47	53	63	68	62	74
2010	71	68	54	40	50	36	44	37	40	52	35	24
2011	23	13	11	5	2	0	0	0	0	0	0	0
Wave 11 (survey year 2012)												
2010	0	0	0	2	5	6	2	8	9	16	11	23
2011	34	23	42	33	40	47	44	49	43	67	70	58
2012	67	48	61	56	30	25	36	27	10	22	10	5
2013	6	7	3	0	0	0	0	0	0	0	0	0
Wave 12 (survey year 2014)												
2012	0	0	0	0	0	7	12	22	18	29	41	44
2013	45	49	60	54	37	53	32	48	61	63	66	53
2014	67	57	51	49	32	24	20	19	15	17	8	5

Note: The years in each wave with less than 10 deaths are omitted from the table.

A.3 List of variables

This section introduces the variables selected from the CLHLS and the HRS. The CLHLS data downloaded from Zeng et al. (2017) contains seven datasets (Table A.3). Most variable names in each dataset follow the convention of a name followed by an underscore and one or two digits denoting the interview year (Table A.4). Some variable names, especially those related to interview dates, lack consistency and need to be cleaned. After cleaning the variable names, the seven datasets are combined into one longitudinal dataset for our analysis. The code along with the accompanying documentation on the data cleaning process is available at `https://sites.google.com/view/mxu/code`.

Table A.3. The CLHLS dataset downloaded from Zeng et al. (2017).

Dataset name	No. of observations	No. of new subjects
DS1 1998-2014 Longitudinal Data, Version 1	9,093	9,093
DS2 2000-2014 Longitudinal Data, Version 1	11,199	6,368
DS3 2002-2014 Longitudinal Data, Version 1	16,064	9,749
DS4 2005-2014 Longitudinal Data, Version 1	15,638	7,463
DS5 2008-2014 Longitudinal Data, Version 1	16,954	9,482
DS6 2011-2014 Longitudinal Data, Version 1	9,765	1,340
DS7 2014 Cross-Sectional Data, Version 1	7,192	1,125
Total	85,905	44,620

Table A.4. The interview wave suffix used in variable names in the CLHLS.

Interview year	1998-99	2000	2002	2005	2008-09	2011-12	2014
Suffix*	`9899`	`_0`	`_2`	`_5`	`_8`	`_11`	`_14`

* If there is no year digit suffix, the variable corresponds to the earliest interview wave in that particular dataset.

Table A.5 shows the variable names selected from the CLHLS dataset. Note that not all variables are listed as some variable names vary by the datasets. We refer the readers to the accompanying documentation of the data cleaning code for a complete list.

Table A.5. Variables selected from the CLHLS datasets.

Variable	Description
ID	Unique identifier of each individual
A1	Gender
RESIDENC*	Residence
V_BIRTHMO	Birth month
V_BIRTHYR	Birth year
DTHxx_yy†	Status of survival, death, or lost to follow-up from xx to yy waves
Interview date	
YEARIN*	Interview year
MONTHIN*	Interview month
DAYIN*	Interview day
Death date‡	
DyVYEAR	Death year
DyMONTH	Death month
DyVDAY	Death day
Activities of daily living§	
E1	Need assistance: Bathing
E2	Need assistance: Dressing
E3	Need assistance: Toileting
E4	Need assistance: Transferring
E5	Need assistance: Continence
E6	Need assistance: Feeding

* Not all variables are listed due to space limit. See the accompanying documentation of the code (available at https://sites.google.com/view/mxu/code) for more details.

† $(\texttt{xx}, \texttt{yy}) \in \{(98, 00), (00, 02), (02, 05), (05, 08), (08, 11), (11, 14)\}$.

‡ y in the following three variables take the value of $0, 2, 5, 8, 11,$ or 14 depending on the interview wave in which the death was reported.

§ The following six variables have suffix that follows the rule in Table A.4.

The HRS data downloaded from RAND HRS Longitudinal File 2016 (V2) (2020) is a single dataset that contains cleaned variables with consistent naming conventions. We selected the variables listed in Table A.6 for our analysis.

Table A.6. Variables selected from RAND HRS Longitudinal File 2016 (V2) (2020).

Variable	Description
Time independent	
`HHIDPN`	Unique identifier of each individual
`RABYEAR`	Birth year
`RABMONTH`	Birth month
`RABDATE`	Birth date
`RADYEAR`	Death year
`RADMONTH`	Death month
`RADDATE`	Death date
`RAGENDER`	Gender
Time dependent*	
`RxIWSTAT`	Interview status
`RxIWEND`	Interview end date
`RxWALKRA`	Some difficulty: Walking across room
`RxDRESSA`	Some difficulty: Dressing
`RxBATHA`	Some difficulty: Bathing, shower
`RxEATA`	Some difficulty: Eating
`RxBEDA`	Some difficulty: Get in/out bed
`RxTOILTA`	Some difficulty: Using the toilet

* `x` in the following variables represents the interview wave. For example, `x = 4` in the 1998 survey, which is the fourth wave.

A.4 Summary statistics

Table A.7. Summary statistics of the selected data samples. The Gender column shows the proportion of females. The Health State columns show the proportion of individuals in each health state.

Survey year	Gender	Health State			Age		No. of
	Female	Healthy (%)	Disabled (%)	Dead (%)	Mean	Std	individuals
Selected CLHLS sample*							
1998	0.60	76.13	23.87	0.00	92.36	7.68	8,140
2000	0.59	59.77	15.57	24.67	92.62	7.77	13,533
2002†	0.58	67.25	14.20	18.55	88.21	11.39	17,976
2005	0.58	60.57	10.45	28.98	88.52	11.63	19,846
2008-09	0.58	64.02	10.15	25.83	88.82	11.47	20,073
2011-12	0.57	52.06	9.72	38.23	89.17	11.34	14,665
2014	0.54	58.26	9.59	32.15	87.87	10.93	8,277
Selected HRS sample*							
1998	0.58	89.89	10.11	0.00	67.05	10.53	19,156
2000	0.58	84.57	9.62	5.81	68.99	10.55	19,168
2002	0.58	83.44	9.86	6.70	70.15	10.10	18,095
2004	0.58	84.11	9.62	6.26	70.18	10.28	18,010
2006	0.58	82.40	10.54	7.05	71.39	9.87	16,872
2008	0.58	82.05	10.54	7.41	72.58	9.50	15,765
2010	0.58	78.69	11.80	9.51	73.52	9.28	15,360
2012	0.58	80.70	11.81	7.49	74.33	8.80	13,954
2014	0.58	78.30	12.52	9.18	75.48	8.49	12,632

* Deaths occurred in 2014 are included in the sample.

† The survey expanded to those aged 65 and above in 2002.

A.5 Proportional hazard assumption

Figure A.3 plots the crude transition rates by urban-rural residence in the CLHLS sample and confirms the reasonableness of the proportional hazard assumption.

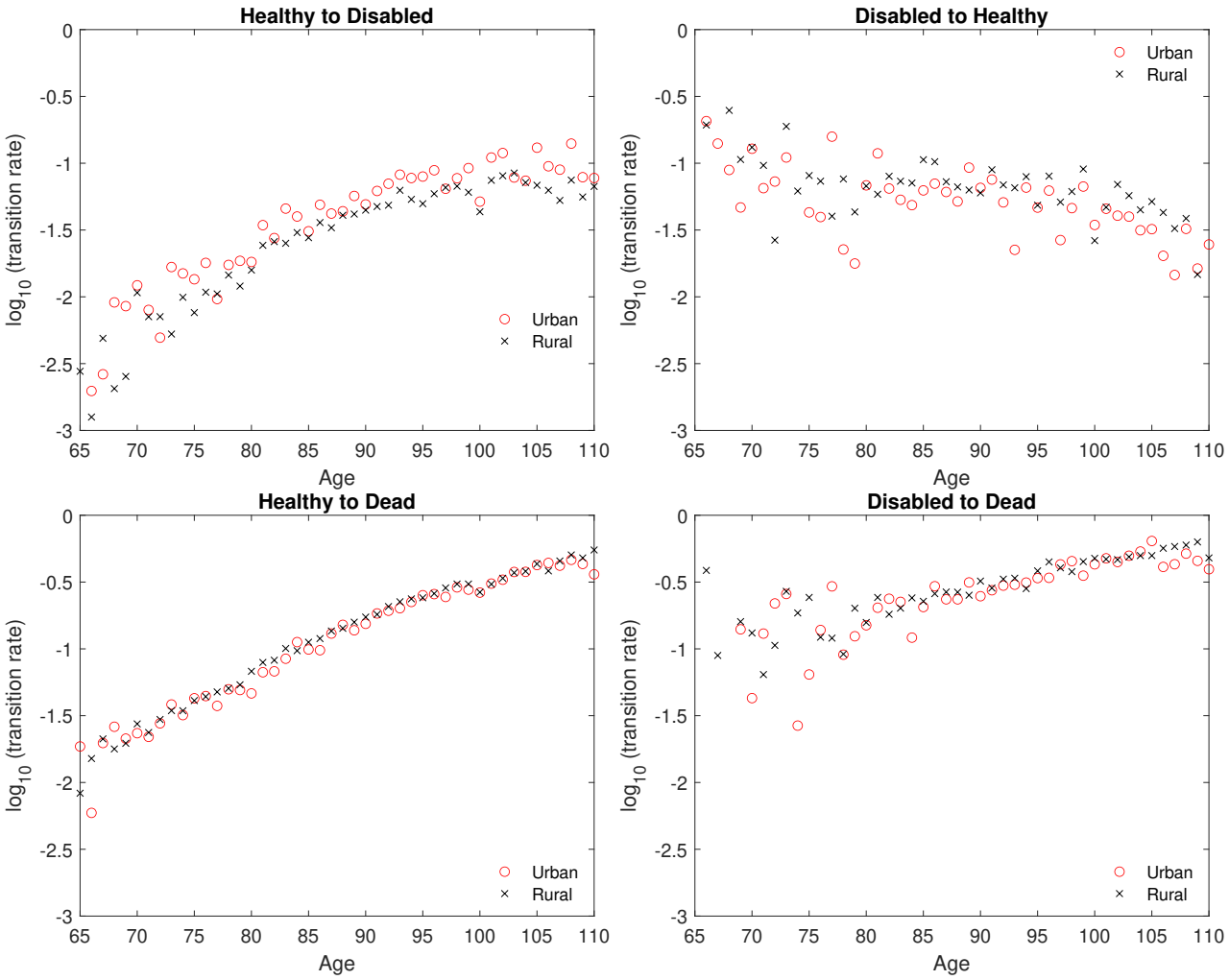

Figure A.3. Crude health transition rates by urban-rural residence in the selected CLHLS sample.

B Supplementary Model Comparison Results

B.1 Health transition rates

Figure B.1 compares the fitted rates with those in Li et al. (2017) and Sherris and Wei (2021) for males based on the HRS data.

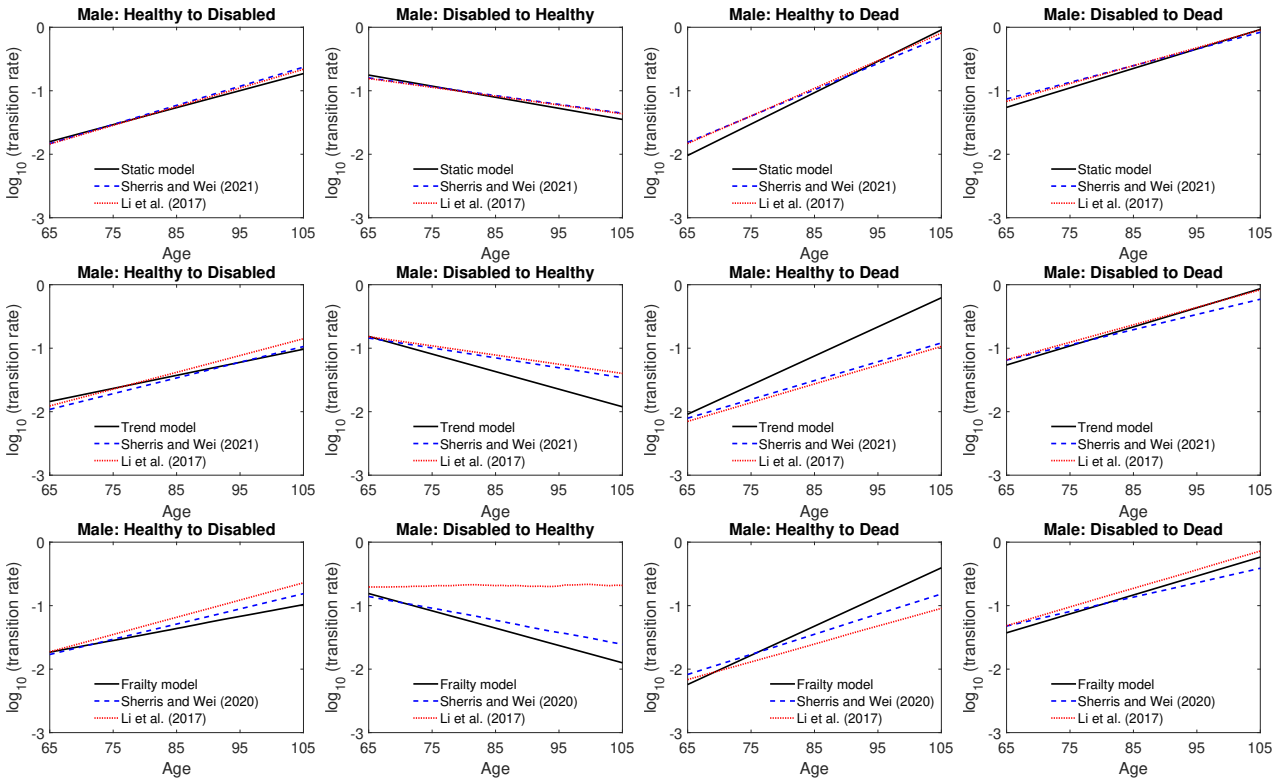

Figure B.1. Compare the estimated transition rates with Sherris and Wei (2021) and Li et al. (2017). The average transition rate is shown for the frailty model. The rates apply to a cohort of males in the U.S. who were 65 in 2010.

B.2 Life expectancy

We have compared our estimated transition rates with prior studies in Section 5. This section compares the implied life expectancy derived from our estimated transition model to quantify the impact of these differences. Table B.1 compares the life expectancy with the United Nations (2019) estimates. The United Nations (2019) estimates are based on the period life tables and average out over people of different health status, so for comparison we use our estimates from the static model and take a weighted average across initially healthy and disabled individuals. Allowing for the time period of the estimation, Table B.1 shows that the static life expectancy estimates for the U.S. population match well to the United Nations (2019) estimates, while those for the Chinese population, especially the male population, appear higher than the United Nations (2019) estimates would suggest.

To understand the reason for this difference, we show the disability prevalence rates from different Chinese data sources in Table B.2. The studies in Table B.2 vary slightly in definition of disability, but overall it is defined as having difficulty in performing at least one of the ADLs, similar to our definition. Among the three studies in Table B.2, Zimmer et al. (2015) use the CLHLS and find the lowest disability prevalence rates controlling for age and gender. This shows that the individuals in the CLHLS have lower disability prevalence rates than the population. The young- to middle-old in the CLHLS are healthier than the general population in China. This accounts for the higher Chinese life expectancy for our model, estimated based on the CLHLS, compared with the population.

Table B.1. Life expectancy of the static model compared to the United Nations (2019) estimates.

	65				75			
	China		U.S.		China		U.S.	
	Female	Male	Female	Male	Female	Male	Female	Male
Static model†	16.76	15.02	20.17	17.69	10.86	9.51	12.73	10.68
United Nations (2019) estimates‡								
1995-2000	15.40	12.82	19.09	15.78	8.92	7.36	12.04	9.68
2000-2005	15.58	13.36	19.35	16.50	9.03	7.56	12.14	10.10
2005-2010	16.02	13.54	20.12	17.47	9.38	7.70	12.74	10.84
2010-2015	16.80	13.86	20.66	18.09	10.03	8.00	13.16	11.37
2015-2020	17.80	14.68	20.94	18.37	10.80	8.59	13.42	11.68

† The life expectancy is a weighted average across initially healthy and disabled individuals, weighted by the exposure years in healthy and disabled states at age 65 or 75 in each gender category.

‡ Accessed 13 October 2020. `https://population.un.org/wpp/Download/Standard/Mortality/`

Table B.2. Estimated disability prevalence rates among the Chinese elderly.

Liang et al. (2014)†	1997	2000	2004	2006
	Both genders combined			
60 – 69	7.4%	6.0%	5.3%	4.6%
70 – 79	16.6%	18.1%	15.2%	13.1%

Zhang and Wei (2015)‡	2010	
	Female	Male
60 – 64	5.3%	6.9%
65 – 69	7.9%	7.8%
70 – 74	13.62%	10.50%
75 – 79	16.54%	15.57%

Zimmer et al. (2015)§	2002-05		2008-11	
	Female	Male	Female	Male
65 – 69	2.8%	4.4%	3.3%	3.5%
70 – 74	7.1%	5.1%	6.5%	5.6%
75 – 79	10.7%	9.6%	9.0%	8.5%

† Liang et al. (2014) use the data from China Health and Nutrition Survey. Someone who requires assistance or is unable to perform at least one of the five ADLs is considered disabled. The five ADLs are bathing, dressing, toileting, feeding, and transferring.

‡ Zhang and Wei (2015) use the data from the Sample Survey of the Aged Population in Urban/Rural China (SSAPUR) and China Health and Retirement Longitudinal Study (CHARLS). Someone who is unable to conduct one or more of the five ADLs is considered disabled. The five ADLs are bathing, dressing, toileting, getting up from a bed and chair, and eating

§ Zimmer et al. (2015) use the data from the CLHLS. Someone who requires assistance or is unable to perform at least one of the six ADLs is considered disabled. The five ADLs are eating, continence, transferring, toileting, dressing, and bathing.

Table B.3 compares our estimated Chinese life expectancy with Hanewald et al. (2019). For the same reasons as when comparing transition rates, we choose our trend model with the residence covariate for comparison. We do not compare results for initially disabled individuals as Hanewald et al. (2019) assume no recovery from the disabled state, whereas our health transition model does.

Table B.3 shows that our life expectancy estimates are similar to, but generally lower, than those in Hanewald et al. (2019). Some of these differences reflect differences in our estimated disability rates which are higher at younger ages (Figure 9) when disabled mortality is much greater than the healthy mortality.

Table B.3. Comparison of total life expectancy (TLE), healthy life expectancy (HLE), and the ratio of healthy life expectancy over total life expectancy (HLE/TLE) between the trend model and Hanewald et al. (2019).

	Trend model with residence				Hanewald et al. (2019)			
	Urban		Rural		Urban		Rural	
	Female	Male	Female	Male	Female	Male	Female	Male
Healthy at 65 in the year 1998								
TLE	17.06	15.26	17.01	15.07	18.24	16.18	17.45	15.75
HLE	15.65	14.32	16.03	14.41	16.85	15.16	16.26	15.03
HLE/TLE	0.918	0.938	0.942	0.956	0.924	0.937	0.932	0.954
Healthy at 65 in the year 2011								
TLE	17.69	15.78	17.45	15.47	18.80	16.52	17.70	16.05
HLE	16.63	15.05	16.70	14.98	17.36	15.16	16.68	15.17
HLE/TLE	0.940	0.954	0.957	0.968	0.923	0.918	0.942	0.945
Healthy at 65 in the year 2020								
TLE	18.04	16.00	17.70	15.66	19.10	16.81	17.83	16.25
HLE	17.25	15.42	17.15	15.24	17.66	15.16	16.93	15.25
HLE/TLE	0.956	0.963	0.969	0.973	0.925	0.902	0.950	0.938

Table B.4 compares our U.S. life expectancy estimates with Li et al. (2017) and Sherris and Wei (2021). Using the static model, we have higher estimates for life expectancy because our static model estimates lower mortality (Figure 10). Our results are consistent with external sources such as United Nations (2019) shown in Table B.1 and Center for Disease Control and Prevention (2016) who report that U.S. life expectancy at 65 years old in the year 2010 was 17.7 for male and 20.3 for female. Using the trend and frailty models, we produce lower estimates because our trend model has a faster estimated growth in mortality with age as explained earlier and shown in Figure 10. Differences are within a reasonable range. Model assumptions and estimation have been improved since the estimation in Li et al. (2017) whose model parameter estimates produce higher estimates from the frailty model, reflecting higher estimated recovery rates and higher uncertainty in these transition rates. The estimation was also improved in Sherris and Wei (2021).

Table B.4. Comparing total life expectancy (TLE), healthy life expectancy (HLE), and the ratio of healthy life expectancy over total life expectancy (HLE/TLE) with Li et al. (2017) and Sherris and Wei (2021). The results apply to a cohort of healthy individuals who were 65 years old in 2010.

	Female			Male		
	Static	Trend	Frailty	Static	Trend	Frailty
TLE	20.41	21.53	21.50	17.87	18.87	18.83
HLE	17.24	18.38	18.33	16.11	17.11	17.04
HLE/TLE	0.845	0.854	0.853	0.902	0.906	0.905
Sherris and Wei (2021)†						
TLE	18.68	22.50	22.13	16.13	19.99	19.57
HLE	15.89	19.50	18.92	14.65	18.22	17.72
HLE/TLE	0.851	0.867	0.855	0.908	0.911	0.905
Li et al. (2017)‡						
TLE	18.96	22.68	23.70	16.23	20.16	21.23
HLE	16.19	19.43	20.79	14.72	18.33	19.56
HLE/TLE	0.854	0.857	0.877	0.907	0.909	0.921

† Sherris and Wei (2021) uses the HRS data from 1998 to 2014.
‡ Li et al. (2017) uses the HRS data from 1998 to 2012.

C Algorithms

Algorithm 1: Simulate health states

Input: Starting age (x) and the maximum attainable age (y)
Transition rate matrices from age x to age y
Required number of simulations, N

Output: N simulated health state paths from age x to age y

initialise the health state at age x;
initialise $\mathbf{S}$; `/* a matrix of size` $(y-x+1)\times N$ `*/`
for $age = x+1$ **to** y **do**
  Transition probability matrix $\mathbf{P} \leftarrow$ Matrix exponential of the transition rate matrix at $age-1$;
  $\mathbf{s}_{\text{old}} \leftarrow N$ simulated health states at $age-1$;
  $n \leftarrow$ an $N \times 1$ matrix of ones;
  $p \leftarrow$ a matrix with N rows where the n^{th} row of p is the k^{th} row of $\mathbf{P}$ where k is the n^{th} element in $\mathbf{s}_{\text{old}}$;
  $\mathbf{S}_{\text{tmp}} \leftarrow$ simulated multinomial random numbers with parameters n (number of trials) and p (multinomial probabilities);
  $\mathbf{S}[age, :] \leftarrow$ the index of 1 in each row of $\mathbf{S}_{\text{tmp}}$;
end
return $\mathbf{S}$;

Algorithm 2: Simulate the future lifetime (random variable) spent in each state

Input: Starting age (x) and the maximum attainable age (y)
N simulated health state paths from age x to age y, $\mathbf{S}$

Output: Future lifetime spent in each state for age x

// *Note:* each column of $\mathbf{S}$ is one simulated path

$\mathbf{s}_0 \leftarrow$ the first row of $\mathbf{S}$; /* initial health states in the simulation */

$\boldsymbol{s} \leftarrow$ unique values in the simulated health state paths ; /* a vector of health states, the first being healthy and the last being dead */

$M \leftarrow$ length of $\boldsymbol{s}$; /* number of health states, including the dead state */

initialise ℓ_m for $m = 1, 2, \cdots, M-1$; /* each ℓ_m is a vector of size N */

for $m = 1$ **to** $M - 1$ **do**

  // ℓ_m (a vector of size N) is the future lifetime in state m

  $\ell_m \leftarrow$ number of elements in each column of $\mathbf{S}$ equal to m;

  // adjust for the assumption that the transition occurs at the middle of the year

  $\ell_m \leftarrow \ell_m - \frac{1}{2} \times (\mathbf{s}_0 == m)$; /* $\mathbf{s}_0 == m$ gives a vector of zeros and/or ones */

end

// $\ell_{\texttt{total}}$ is the total future lifetime

$\ell_{\text{total}} \leftarrow \sum_{m=1}^{M-1} \ell_m$;

return $\ell_1, \ldots, \ell_{M-1}$, ℓ_{total};

D Supplementary Simulation Results

D.1 Estimated transition rates: a cohort comparison

Figure D.1 and Figure D.2 compare the estimated transition rates between the two simulated cohorts (aged 65 in 1998 and aged 65 in 2014) based on the CLHLS sample and the HRS sample, respectively. For the trend model, the mortality rates at age 65 and thereafter are similar for the two cohorts. The impact of trends is more significant for the disability and recovery rates which differ between the two cohorts. This reflects our estimation results in Table 8 that disability and recovery rates show stronger time trends than mortality rates.

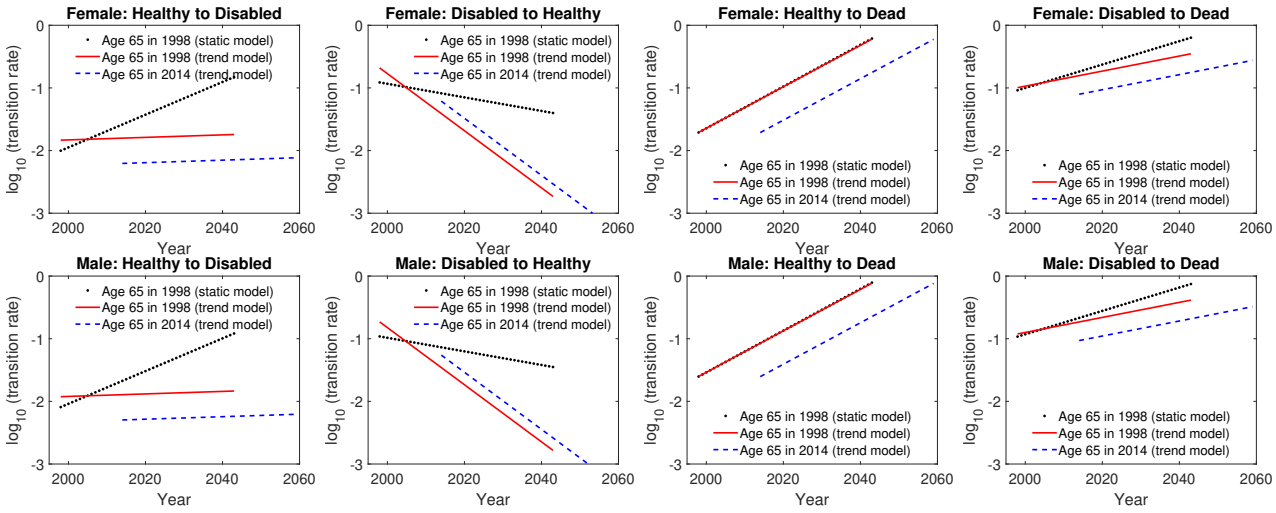

Figure D.1. Comparison of the estimated transition rates between the simulated cohorts assumed age 65 in 1998 and age 65 in 2014. The transition rates are assumed to follow the static model or the trend model. The parameters are estimated based on the CLHLS sample.

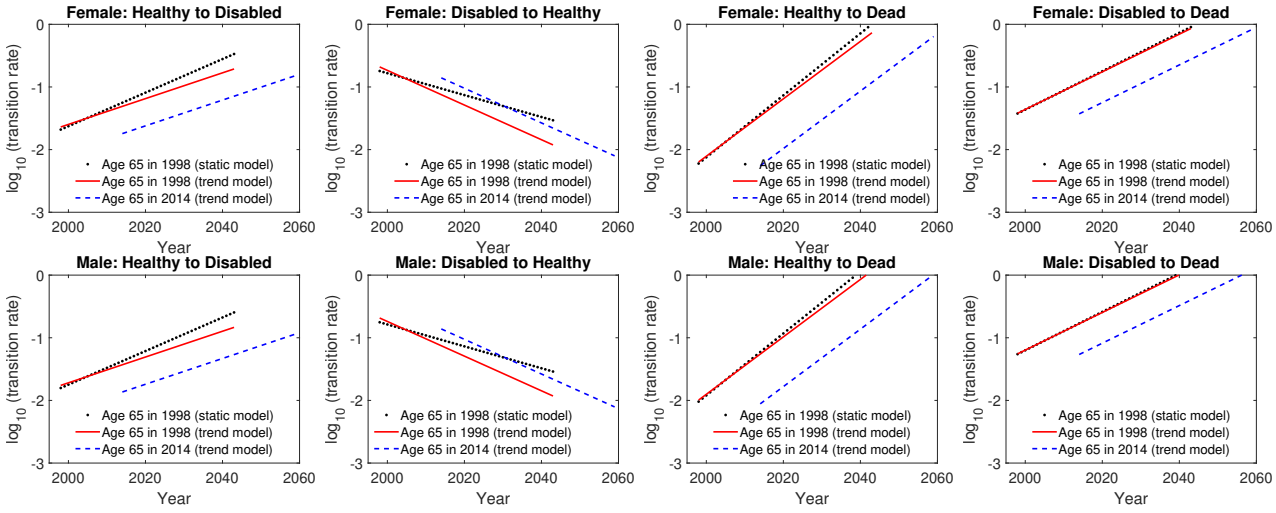

Figure D.2. Comparison of the estimated transition rates between the simulated cohorts assumed age 65 in 1998 and age 65 in 2014. The transition rates are assumed to follow the static model or the trend model. The parameters are estimated based on the HRS sample.

D.2 Survival curves

Figure D.3 to Figure D.6 display the survival curves for the healthy 75-year-old. Table D.1 to Table D.4 display the simulated future lifetime statistics using the frailty model.

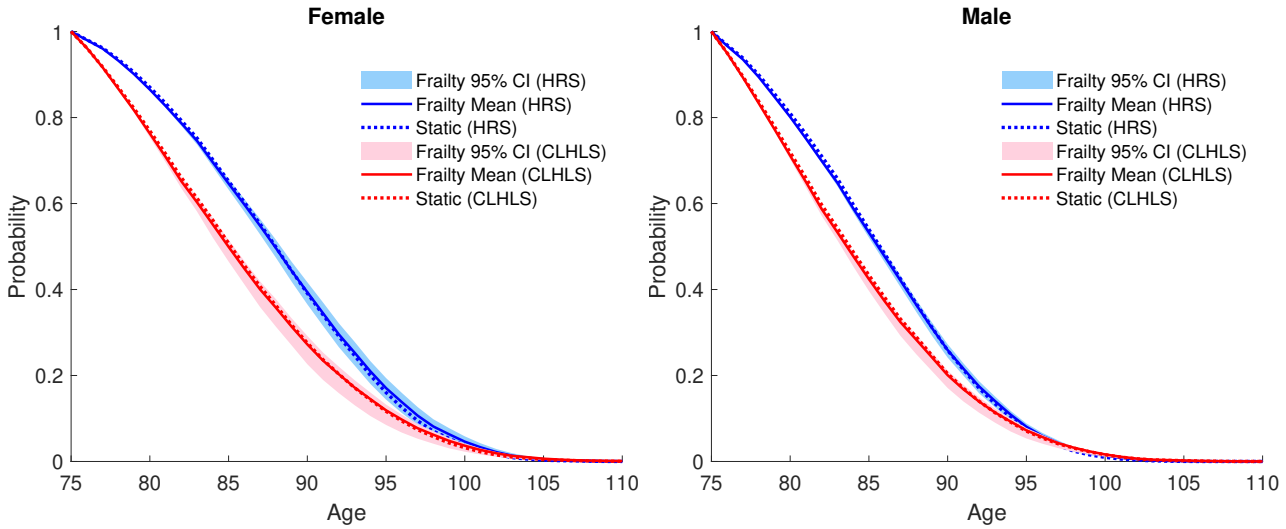

Figure D.3. Survival curves of the static and frailty models for a cohort of individuals who were healthy at age 75 in the year 1998. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

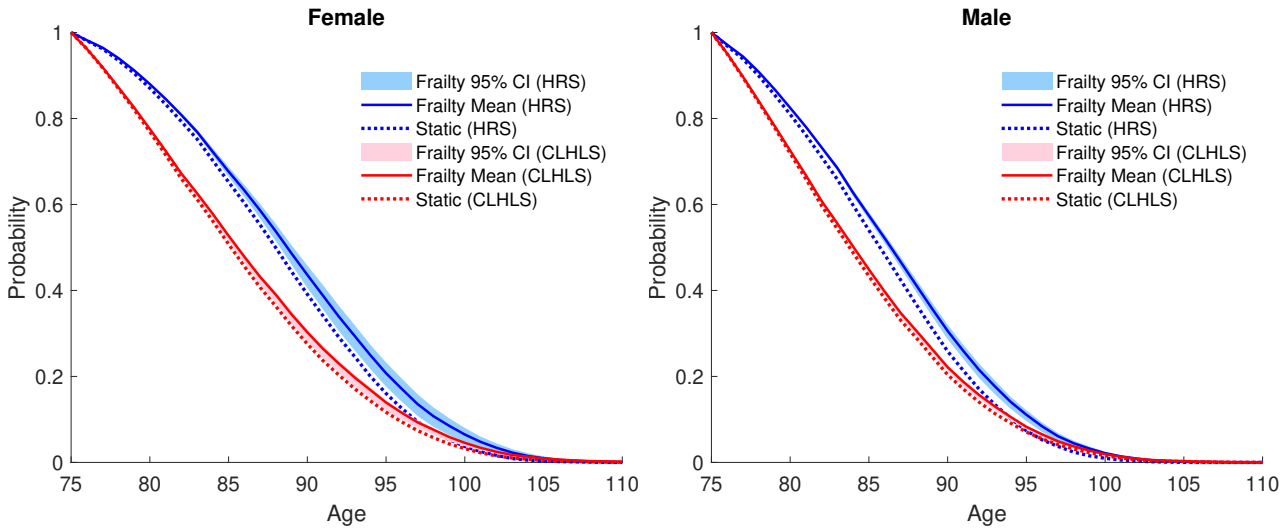

Figure D.4. Survival curves of the static and frailty models for a cohort of individuals who were healthy at age 75 in the year 2014. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

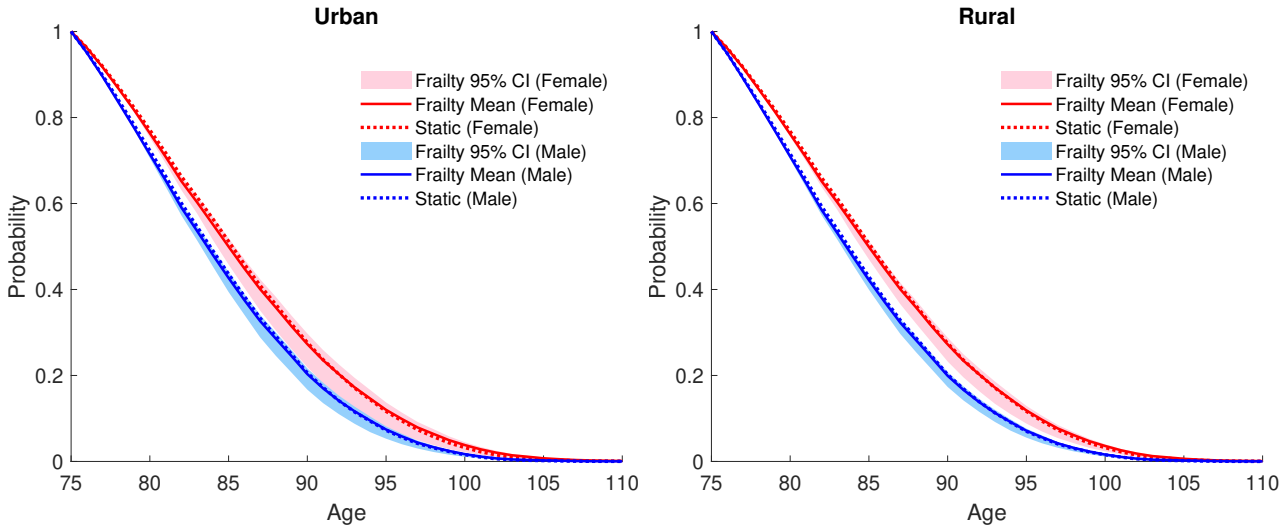

Figure D.5. Survival curves of the static and frailty models (with the residence covariate) for a cohort of individuals who were healthy at age 75 in the year 1998. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

Table D.1. Frailty model: future lifetime statistics for 65-year-old healthy individuals in 1998 and 2014, including mean, 95% confidence interval of the mean in square brackets, standard error of the mean in round brackets, and standard deviation (Std). The maximum attainable age is 110.

	CLHLS		HRS	
	Female	Male	Female	Male
1998				
Total future lifetime				
Mean	16.87 [15.76, 17.26] (0.0030)	15.04 [14.29, 15.30] (0.0027)	20.85 [20.01, 21.50] (0.0028)	18.19 [17.70, 18.53] (0.0026)
Std	9.35	8.69	8.94	8.33
Healthy future lifetime				
Mean	15.66 [13.37, 16.65] (0.0029)	14.22 [12.64, 14.87] (0.0027)	17.74 [16.09, 19.13] (0.0028)	16.46 [15.45, 17.22] (0.0026)
Std	9.21	8.59	8.70	8.24
Disabled future lifetime				
Mean	1.21 [0.58, 2.34] (0.0010)	0.82 [0.39, 1.64] (0.0008)	3.10 [2.37, 3.92] (0.0014)	1.73 [1.31, 2.25] (0.0010)
Std	3.16	2.49	4.48	3.19
Healthy future lifetime over total future life time				
Mean	0.929 [0.870, 0.962] (5E-5)	0.946 [0.902, 0.971] (5E-5)	0.855 [0.815, 0.888] (6E-5)	0.905 [0.877, 0.927] (5E-5)
Std	0.170	0.152	0.202	0.173
Age at onset of disability conditional on becoming disabled				
Mean	75.52 [71.32, 79.52] (0.0052)	74.85 [71.12, 78.76] (0.0055)	79.37 [78.38, 80.32] (0.0037)	78.41 [77.43, 79.32] (0.0041)
Std	7.09	6.56	8.47	7.82
2014				
Total future lifetime				
Mean	17.47 [16.97, 17.63] (0.0030)	15.53 [15.26, 15.62] (0.0028)	21.81 [20.91, 22.52] (0.0029)	19.11 [18.58, 19.51] (0.0027)
Std	9.53	8.85	9.14	8.58
Healthy future lifetime				
Mean	16.59 [14.95, 17.18] (0.0030)	14.92 [13.93, 15.24] (0.0028)	18.78 [17.10, 20.19] (0.0029)	17.46 [16.45, 18.26] (0.0027)
Std	9.49	8.81	9.27	8.67
Disabled future lifetime				
Mean	0.88 [0.36, 1.99] (0.0010)	0.61 [0.26, 1.34] (0.0008)	3.02 [2.32, 3.81] (0.0015)	1.65 [1.24, 2.13] (0.0010)
Std	3.21	2.57	4.63	3.25
Healthy future lifetime over total future life time				
Mean	0.953 [0.901, 0.979] (5E-5)	0.964 [0.928, 0.983] (4E-5)	0.860 [0.823, 0.891] (7E-5)	0.911 [0.886, 0.931] (6E-5)
Std	0.153	0.136	0.209	0.176
Age at onset of disability conditional on becoming disabled				
Mean	76.18 [71.43, 81.17] (0.0077)	75.03 [70.90, 79.77] (0.0077)	80.54 [79.43, 81.59] (0.0041)	79.32 [78.17, 80.32] (0.0045)
Std	7.36	6.56	8.95	8.20

Table D.2. Frailty model: future lifetime statistics for 75-year-old healthy individuals in 1998 and 2014, including mean, 95% confidence interval of the mean in square brackets, standard error of the mean in round brackets, and standard deviation (Std). The maximum attainable age is 110.

	CLHLS		HRS	
	Female	Male	Female	Male
1998				
Total future lifetime				
Mean	10.91 [10.26, 11.20] (0.0022)	9.55 [9.12, 9.71] (0.0020)	13.12 [12.70, 13.47] (0.0022)	10.90 [10.68, 11.06] (0.0019)
Std	7.01	6.38	6.82	6.15
Healthy future lifetime				
Mean	9.86 [8.50, 10.60] (0.0021)	8.85 [7.94, 9.31] (0.0020)	10.59 [9.78, 11.32] (0.0020)	9.55 [9.09, 9.94] (0.0019)
Std	6.77	6.22	6.42	5.95
Disabled future lifetime				
Mean	1.05 [0.60, 1.75] (0.0008)	0.69 [0.38, 1.18] (0.0006)	2.52 [2.15, 2.93] (0.0012)	1.35 [1.13, 1.59] (0.0008)
Std	2.61	2.02	3.73	2.61
Healthy future lifetime over total future life time				
Mean	0.910 [0.858, 0.944] (6E-5)	0.933 [0.894, 0.958] (6E-5)	0.819 [0.790, 0.846] (8E-5)	0.883 [0.864, 0.901] (7E-5)
Std	0.200	0.178	0.249	0.216
Age at onset of disability conditional on becoming disabled				
Mean	82.62 [79.94, 85.02] (0.0036)	82.08 [79.66, 84.48] (0.0039)	84.20 [83.71, 84.68] (0.0026)	83.47 [82.87, 83.99] (0.0029)
Std	5.30	4.89	5.89	5.36
2014				
Total future lifetime				
Mean	11.44 [11.16, 11.54] (0.0023)	9.92 [9.79, 9.96] (0.0021)	13.86 [13.40, 14.24] (0.0022)	11.66 [11.42, 11.85] (0.0020)
Std	7.28	6.55	7.08	6.41
Healthy future lifetime				
Mean	10.68 [9.74, 11.12] (0.0022)	9.45 [8.89, 9.67] (0.0020)	11.44 [10.57, 12.19] (0.0022)	10.37 [9.87, 10.76] (0.0020)
Std	7.10	6.46	6.89	6.34
Disabled future lifetime				
Mean	0.76 [0.37, 1.42] (0.0008)	0.46 [0.25, 0.89] (0.0006)	2.43 [2.04, 2.84] (0.0012)	1.29 [1.08, 1.54] (0.0008)
Std	2.61	1.93	3.82	2.65
Healthy future lifetime over total future life time				
Mean	0.944 [0.900, 0.970] (5E-5)	0.961 [0.929, 0.977] (5E-5)	0.831 [0.803, 0.857] (8E-5)	0.892 [0.872, 0.908] (7E-5)
Std	0.171	0.147	0.248	0.213
Age at onset of disability conditional on becoming disabled				
Mean	83.19 [79.95, 86.49] (0.0053)	82.29 [79.62, 85.54] (0.0057)	85.10 [84.49, 85.66] (0.0030)	84.26 [83.62, 84.83] (0.0033)
Std	5.54	4.96	6.36	5.82

Table D.3. Frailty model with residence: future lifetime statistics for 65-year-old healthy individuals in 1998 and 2014, including mean, 95% confidence interval of the mean in square brackets, standard error of the mean in round brackets, and standard deviation (Std). The maximum attainable age is 110.

	Urban		Rural	
	Female	Male	Female	Male
1998				
Total future lifetime				
Mean	16.88 [15.56, 17.39] (0.0030)	15.13 [14.22, 15.46] (0.0028)	16.87 [15.90, 17.18] (0.0030)	14.98 [14.36, 15.18] (0.0027)
Std	9.37	8.73	9.33	8.68
Healthy future lifetime				
Mean	15.42 [12.67, 16.69] (0.0029)	14.13 [12.21, 14.95] (0.0027)	15.83 [13.81, 16.66] (0.0029)	14.28 [12.90, 14.80] (0.0027)
Std	9.20	8.61	9.18	8.57
Disabled future lifetime				
Mean	1.46 [0.68, 2.81] (0.0011)	1.01 [0.48, 2.00] (0.0009)	1.04 [0.47, 2.11] (0.0009)	0.69 [0.32, 1.42] (0.0007)
Std	3.49	2.79	2.87	2.25
Healthy future lifetime over total future life time				
Mean	0.915 [0.844, 0.956] (6E-5)	0.934 [0.881, 0.964] (5E-5)	0.940 [0.886, 0.969] (5E-5)	0.955 [0.915, 0.976] (4E-5)
Std	0.186	0.167	0.154	0.138
Age at onset of disability conditional on becoming disabled				
Mean	75.56 [71.56, 79.34] (0.0049)	74.86 [71.00, 78.70] (0.0051)	75.81 [71.44, 80.06] (0.0057)	75.14 [71.10, 79.18] (0.0061)
Std	7.13	6.59	7.14	6.73
2014				
Total future lifetime				
Mean	17.65 [17.01, 17.85] (0.0030)	15.73 [15.35, 15.85] (0.0028)	17.40 [16.97, 17.55] (0.0030)	15.43 [15.22, 15.52] (0.0028)
Std	9.62	8.93	9.52	8.83
Healthy future lifetime				
Mean	16.54 [14.46, 17.33] (0.0030)	14.96 [13.68, 15.39] (0.0028)	16.61 [15.11, 17.11] (0.0030)	14.90 [14.02, 15.17] (0.0028)
Std	9.55	8.87	9.46	8.79
Disabled future lifetime				
Mean	1.11 [0.41, 2.50] (0.0011)	0.76 [0.35, 1.69] (0.0009)	0.80 [0.32, 1.83] (0.0010)	0.53 [0.22, 1.22] (0.0007)
Std	3.58	2.90	3.02	2.34
Healthy future lifetime over total future life time				
Mean	0.942 [0.876, 0.975] (5E-5)	0.956 [0.911, 0.978] (5E-5)	0.958 [0.908, 0.981] (5E-5)	0.969 [0.935, 0.985] (4E-5)
Std	0.169	0.150	0.145	0.126
Age at onset of disability conditional on becoming disabled				
Mean	76.22 [71.42, 81.24] (0.0070)	75.25 [71.04, 80.04] (0.0072)	76.33 [71.33, 81.45] (0.0080)	75.23 [71.23, 80.09] (0.0083)
Std	7.40	6.74	7.36	6.63

Table D.4. Frailty model with residence: future lifetime statistics for 75-year-old healthy individuals in 1998 and 2014, including mean, 95% confidence interval of the mean in square brackets, standard error of the mean in round brackets, and standard deviation (Std). The maximum attainable age is 110.

	Urban		Rural	
	Female	Male	Female	Male
1998				
Total future lifetime				
Mean	10.94 [10.15, 11.31] (0.0022)	9.60 [9.09, 9.80] (0.0020)	10.90 [10.34, 11.13] (0.0022)	9.51 [9.15, 9.64] (0.0020)
Std	7.04	6.40	7.00	6.37
Healthy future lifetime				
Mean	9.67 [8.06, 10.58] (0.0021)	8.78 [7.67, 9.34] (0.0020)	9.99 [8.79, 10.61] (0.0021)	8.93 [8.12, 9.30] (0.0020)
Std	6.72	6.21	6.77	6.22
Disabled future lifetime				
Mean	1.27 [0.71, 2.09] (0.0009)	0.83 [0.44, 1.43] (0.0007)	0.91 [0.51, 1.57] (0.0008)	0.58 [0.31, 1.03] (0.0006)
Std	2.88	2.22	2.40	1.83
Healthy future lifetime over total future life time				
Mean	0.893 [0.832, 0.934] (7E-5)	0.921 [0.874, 0.951] (6E-5)	0.922 [0.875, 0.952] (6E-5)	0.944 [0.908, 0.965] (5E-5)
Std	0.216	0.192	0.185	0.162
Age at onset of disability conditional on becoming disabled				
Mean	82.64 [79.98, 84.86] (0.0034)	82.08 [79.58, 84.43] (0.0036)	82.80 [80.09, 85.35] (0.0039)	82.32 [79.84, 84.79] (0.0043)
Std	5.35	4.90	5.41	5.02
2014				
Total future lifetime				
Mean	11.57 [11.20, 11.71] (0.0023)	10.07 [9.90, 10.13] (0.0021)	11.38 [11.14, 11.46] (0.0023)	9.85 [9.75, 9.88] (0.0021)
Std	7.36	6.62	7.25	6.53
Healthy future lifetime				
Mean	10.63 [9.45, 11.20] (0.0023)	9.47 [8.75, 9.76] (0.0021)	10.70 [9.82, 11.09] (0.0022)	9.44 [8.94, 9.62] (0.0020)
Std	7.12	6.50	7.08	6.44
Disabled future lifetime				
Mean	0.94 [0.47, 1.76] (0.0009)	0.59 [0.32, 1.15] (0.0007)	0.68 [0.32, 1.32] (0.0008)	0.41 [0.21, 0.81] (0.0006)
Std	2.92	2.20	2.45	1.80
Healthy future lifetime over total future life time				
Mean	0.932 [0.877, 0.963] (6E-5)	0.950 [0.910, 0.971] (5E-5)	0.949 [0.908, 0.973] (5E-5)	0.965 [0.936, 0.981] (4E-5)
Std	0.186	0.166	0.162	0.138
Age at onset of disability conditional on becoming disabled				
Mean	83.37 [80.30, 86.47] (0.0050)	82.43 [79.54, 85.65] (0.0053)	83.24 [80.06, 86.71] (0.0055)	82.42 [79.76, 85.73] (0.0060)
Std	5.73	5.20	5.54	5.01

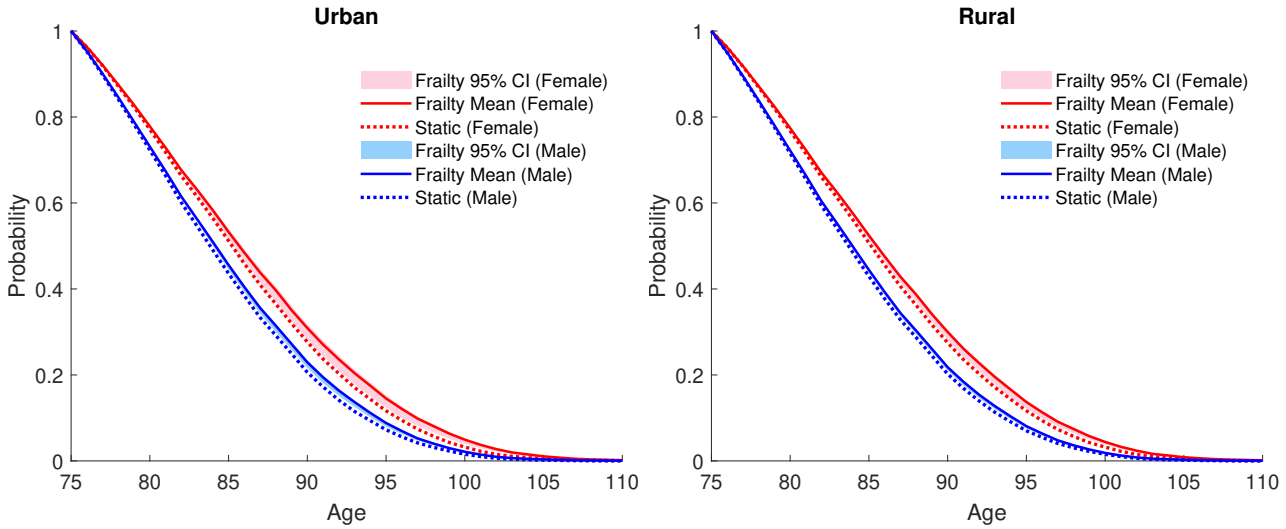

Figure D.6. Survival curves of the static and frailty models (with the residence covariate) for a cohort of individuals who were healthy at age 75 in the year 2014. Survival curve of the trend model virtually overlaps with the mean of the frailty model. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated survival curves from the frailty model. Frailty Mean is determined by the sample mean of the simulated survival curves from the frailty model.

D.3 Health distribution

Figure D.7 to Figure D.10 show the probability of being disabled for a cohort of 75-year-old healthy individuals.

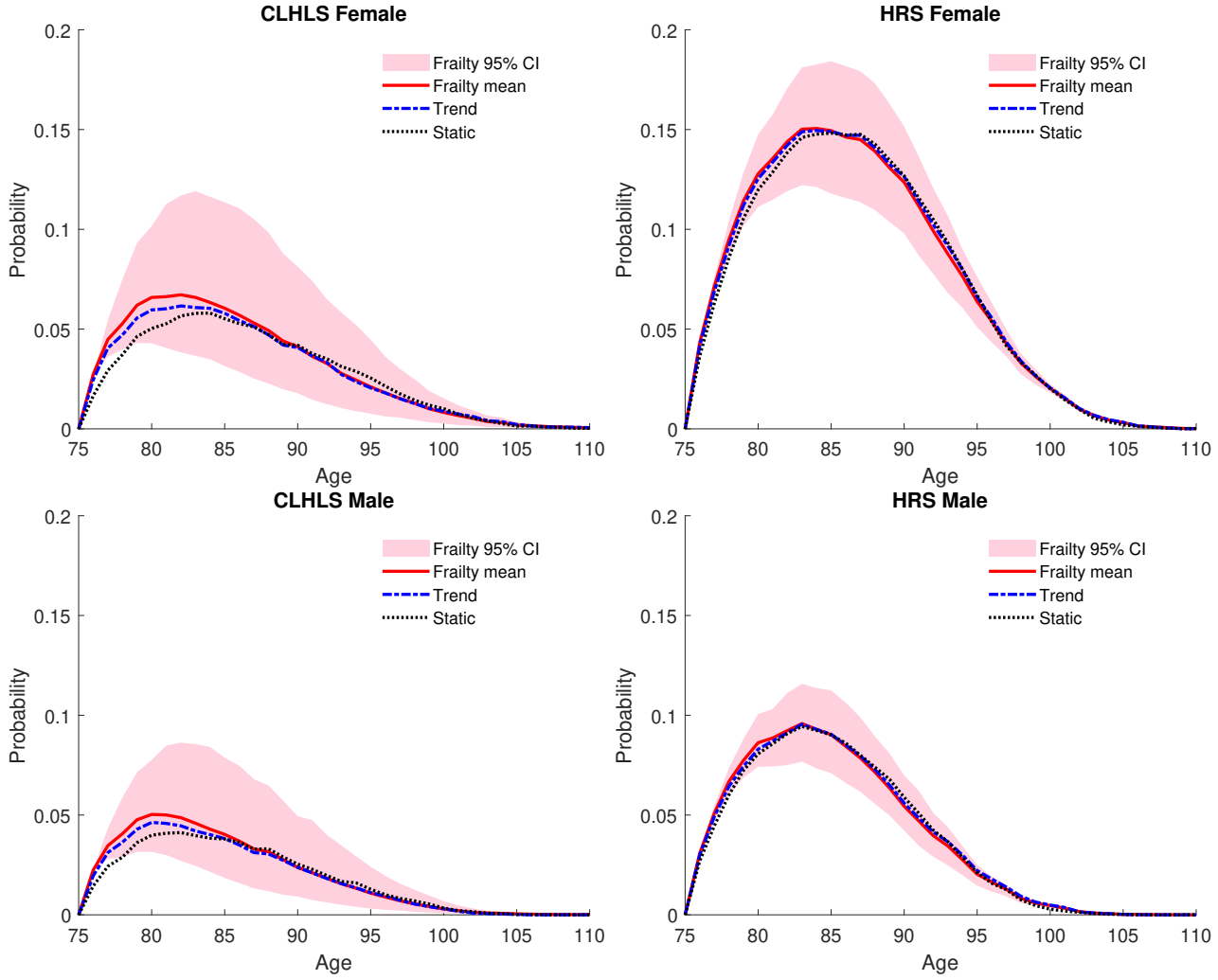

Figure D.7. Probability of being in the disabled state for a cohort of individuals who were healthy at age 75 in the year 1998. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.

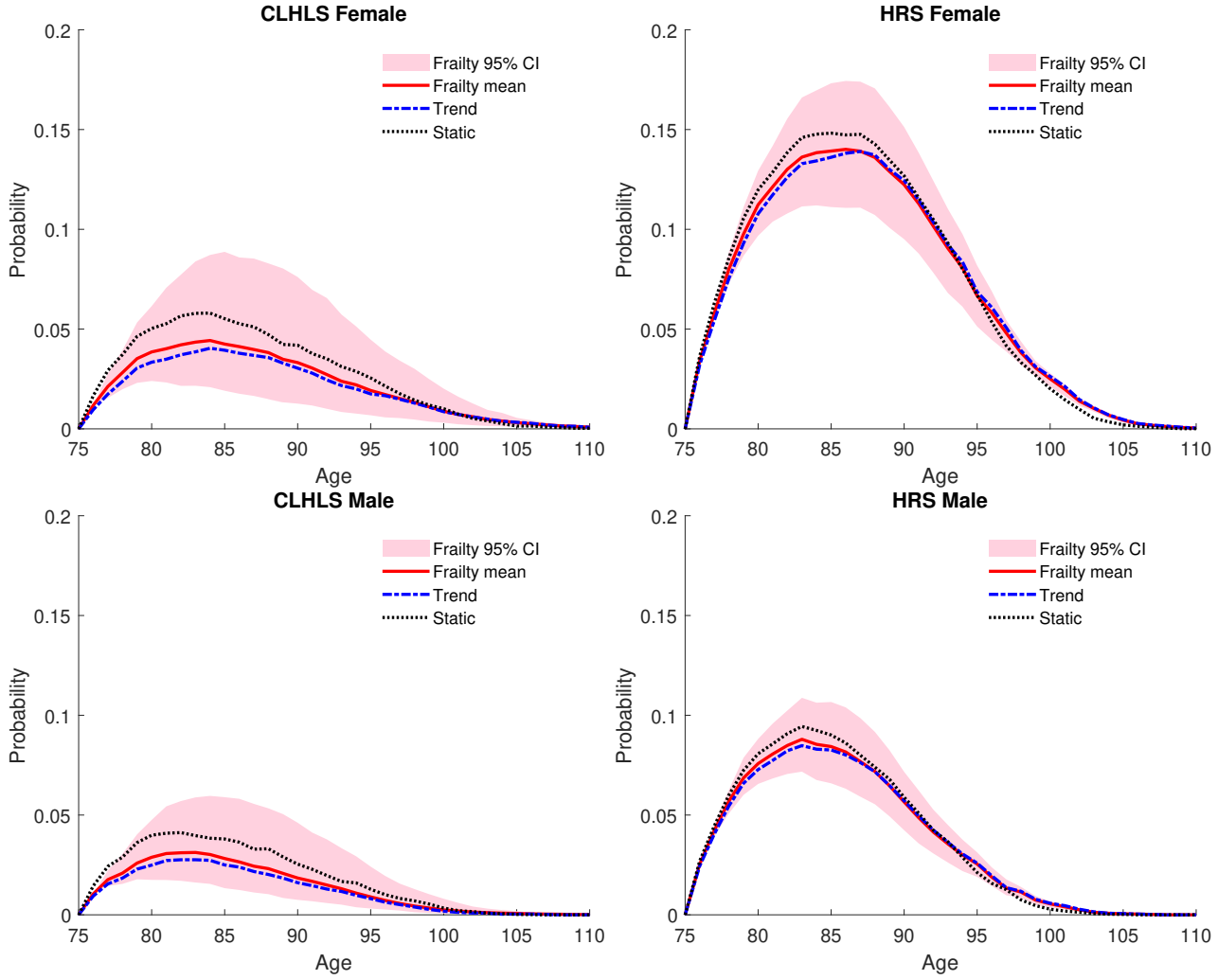

Figure D.8. Probability of being in the disabled state for a cohort of individuals who were healthy at age 75 in the year 2014. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.

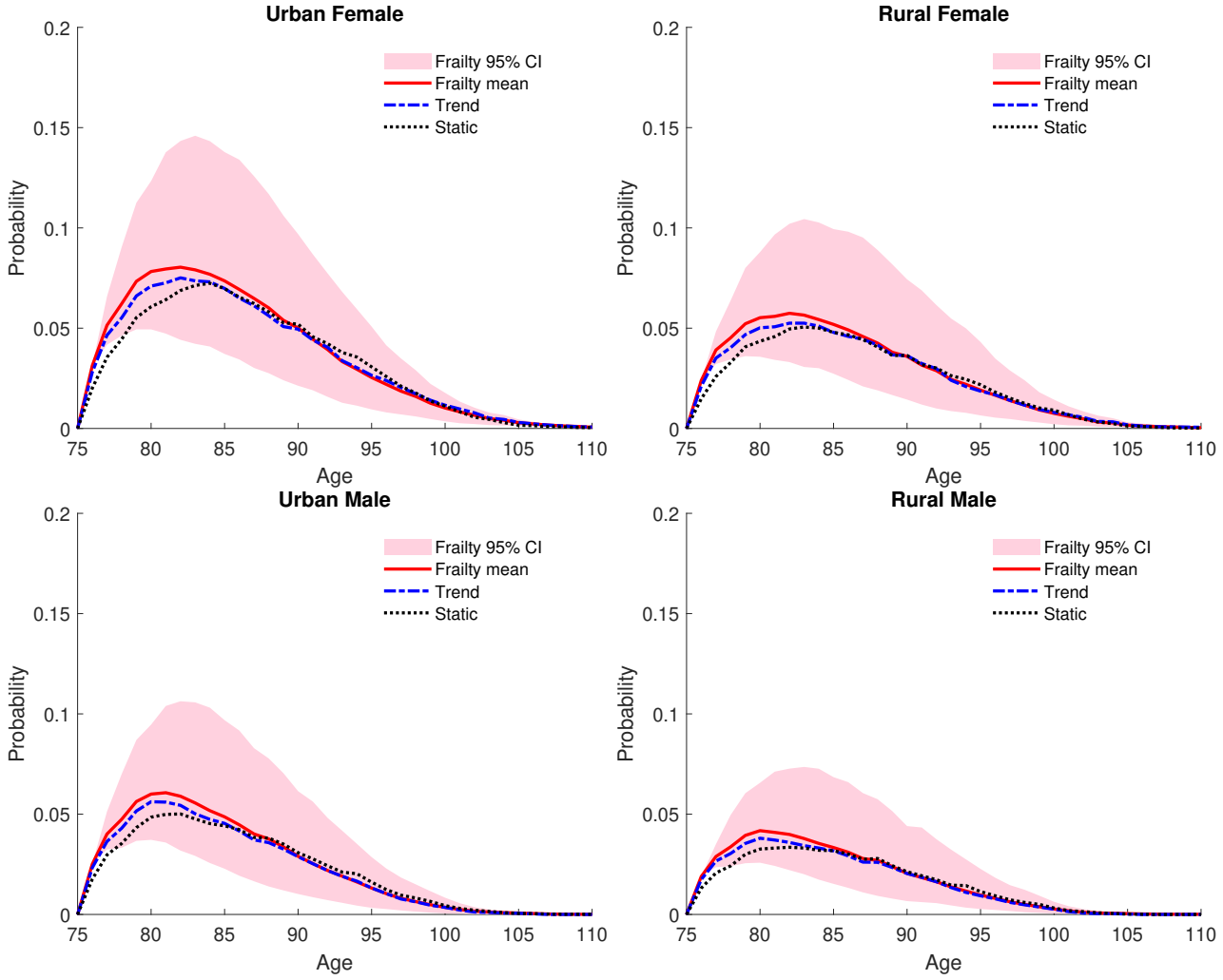

Figure D.9. Probability of being in the disabled state for a cohort of individuals who were healthy at age 75 in the year 1998. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.

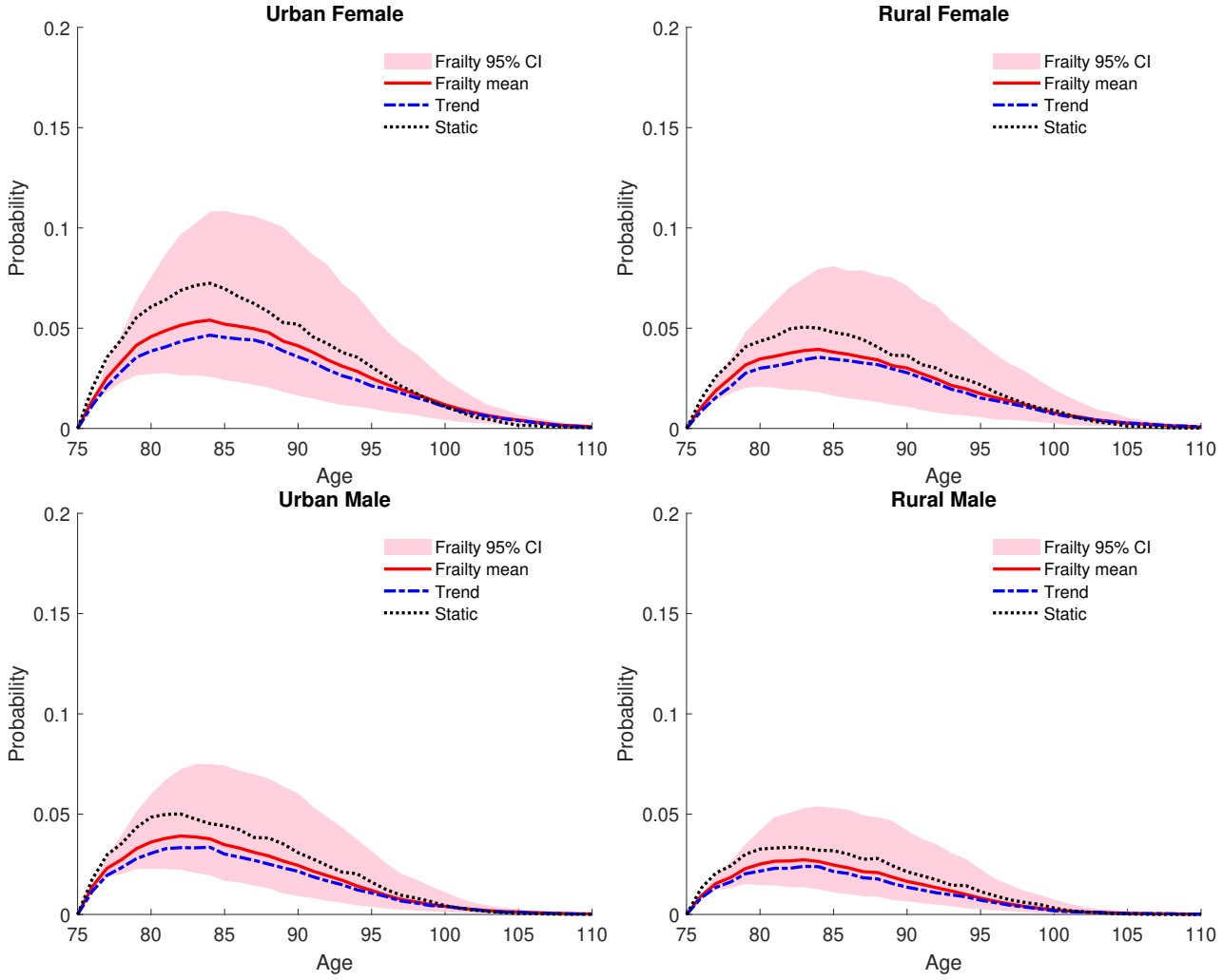

Figure D.10. Probability of being in the disabled state for a cohort of individuals who were healthy at age 75 in the year 2014. Frailty 95% CI is determined by the 2.5^{th} and 97.5^{th} percentiles of the simulated probabilities from the frailty model. Frailty mean is determined by the sample mean of the simulated probabilities from the frailty model.