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Estimating Healthy Life Expectancy: A Province-by-Province Study for China

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Abstract

With rapid economic growth and medical advances, longevity and health in China have been continuously improving in recent decades. However, health inequalities across Chinese provinces are still large. In this paper, we provide a province-by-province analysis of healthy life expectancy at birth for China. We develop a predictive multiple regression model utilizing information on life expectancy, health and socio-economic factors to estimate healthy life expectancy for Chinese provinces. Unlike the standard Sullivan method, the model we propose does not require data on ill-health prevalence rates which are not publicly available for each province. The model is estimated using data from the Global Burden of Disease Study for life expectancy and healthy life expectancy at birth for 139 countries in the years 1990, 2005 and 2013. We assess the predictive ability of the fitted model using appropriate hold-out samples and conclude that the model has good out-of-sample performance. Based on the proposed model, we provide estimates of healthy life expectancy at birth in 2015 for 31 provincial-level regions in China for both males and females. We then discuss the implications of our results for the design of public policies and the development of insurance and banking products in China.

Keywords: Healthy life expectancy; Predictive regression modeling; Health inequality; China

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1 Introduction

Since introduced by Sanders in 1964, healthy life expectancy (HLE) has become an important and popular measure to monitor population health. It is used to measure the future lifetime of an individual in healthy condition. By taking both mortality and morbidity into account, HLE captures the quality as well as the quantity of life. While HLE at the national level has been calculated for most countries in the world (see Jagger and Robine, 2011, for a summary), it is also important to study HLE for different subregions within a country. Analyses of subregional HLE provide a more complete picture of population health in a country. More importantly, understanding health inequalities across regions assists the design of both public pension policies (e.g., Stevens, 2016; Attias *et al.*, 2016; Godínez-Olivares *et al.*, 2016) and private-market insurance and banking products (e.g., Shao *et al.*, 2015; Ai *et al.*, 2017). This is of particular importance for countries with large disparity in population health across regions.

During the last three decades, HLE in China has been continuously improving (e.g., Zimmer *et al.*, 2015; Luo *et al.*, 2016; Guo, 2017). However, there is a large degree of heterogeneity in population health across provincial-level regions in China which demands further attention. Several studies have explored subregional variations in HLE for developed countries (e.g., Groenewegen *et al.*, 2003; Matthews *et al.*, 2006; Burgio *et al.*, 2009). However, as far as we know, very few studies have focused on the regional disparity in HLE in China (Liu *et al.*, 2010). This is because most earlier studies rely on the Sullivan method to compute HLE, which requires detailed information on age-specific morbidity and mortality rates which are not publicly available at the province level.

In this paper, we develop a new approach to estimating subregional HLE and apply the model to China. We propose a multiple regression model for HLE that does not rely on age-specific regional morbidity data, but rather on longevity and socio-economic variables that are widely available. The proposed model is estimated using data from 139 countries in the years 1990, 2005 and 2013 from a number of international databases including the Global Burden of Disease (GBD) Study, the World Bank and the Organization for Economic Co-operation and Development (OECD). Due to the large variation in health and economic development across Chinese provinces, we treat each provincial-level region in China as a "country". This allows us to use the estimated model to predict provincial-level HLEs for China.

We evaluate the out-of-sample predictive performance of the model by comparing the model-predicted HLE with published HLE figures. We first test whether the model is able to explain the cross-sectional variations in HLE by comparing the model-predicted HLE with the reported HLE for 128 countries in 2010. The results show that our estimates of HLE are in line with the reported HLE for over 96% of the countries included. To test whether the model captures the development of HLE over time, we then compare the model-predicted HLE with the reported HLE for Taiwan in the years 2005, 2010 and 2013. We find that the HLE predictions for Taiwan based on the proposed model also have a very high level of accuracy. These results give us confidence in applying our model to provincial-level regions in China.

Using the estimated model, we calculate HLE for 31 provincial-level administrative units in China in 2015. The results show that HLE varies by more than 10 years across Chinese provinces for both males and females. The estimated male HLE in Beijing is 70.5 years which is similar to developed countries in Europe such as Sweden. In contrast, Yunnan's estimated male HLE of only 60.4 years is comparable to African developing countries such as Egypt. Our research provides a new framework for estimating provincial-level HLE for China. The model developed in this paper can also be applied to other countries and regions where detailed mortality and morbidity data are not available.

The rest of the paper is organized as follows. In the next section, we further discuss the background and motivation for our work. We introduce the multiple regression model in Section 3. Section 4 describes the data used in this study. The estimation results, validation tests and provincial-level HLE projections are shown in Section 5. Section 6 concludes the paper and discusses the implications of our research for the design of public policies and the development of insurance and banking products in China.

2 Background and motivation

Depending on how being "healthy" is defined, HLE can be measured in different ways. Examples in the literature include life expectancy in good perceived health (Smith *et al.*, 2008; Brønnum-Hansen, 2005), disease-free life expectancy (Sauvaget *et al.*, 1997; Dubois and Hébert, 2006; Lièvre *et al.*, 2008), disability-free life expectancy (Crimmins *et al.*, 1997; Imai and Soneji, 2007) and active life expectancy (Crimmins *et al.*, 1996; Kaneda *et al.*, 2005; Manton *et al.*, 2006).

A widely used HLE measure is health-adjusted life years (HALE) published by the World Health Organization (WHO). In 2000, the WHO published its first report on the average health situation for 191 countries using HALE as a summary measure.[1] HALE measures the expected years of life living in full health, taking into account severity-weighted disability prevalence estimated in the GBD Study (Murray and Lopez, 1997). In this study, we adopt HALE as the measure of HLE.

HLE is typically computed using the Sullivan method, which requires information on age-specific prevalence rates of ill-health and age-specific mortality rates (Jagger, 1999). Therefore, the biggest challenge of conducting a province-by-province HLE study for China is the lack of high quality age-specific morbidity and mortality data that is publicly available. There are several household-level longitudinal surveys collecting morbidity information in different regions, such as the China Health and Nutrition Survey and the Chinese Longitudinal Healthy Longevity Survey. However, the sample sizes of these surveys are not large enough for provincial-level analysis. The China Disabled Persons' Federation has carried out two National Sample Surveys on Disability in 1987 and 2006. Face-to-face interviews were adopted as the primary data collection method. Detailed information on disabled individuals such as age, gender, residence, education and employment was collected during the interview process. Using the data from these two surveys, Liu *et al.* (2009) studied disability-free life expectancy at age 60 at the national level. Based on the second National Sample Surveys on Disability, Liu *et al.* (2010) computed the disability-free life expectancy at age 60 for 31 provincial-level administrative units in 2006. They found that there is a large degree of variation in HLE across regions with estimates ranging from 11.2 to 20.8 years, which reflects the patterns in regional economic developments.

To date, the study by Liu *et al.* (2010) remains the main reference for regional differences in HLE in China. Since provincial-level information on ill-health rates is sparse, regional variations in HLE across China are still under-researched. As China is rapidly aging, more research in this area is needed to inform policy makers, health care providers and insurance companies in order to identify the differences in the demand for health care and aged care services across China.

It is well known that China's provinces are at very different stages of development (e.g., Heilig,

[1] HALE was originally called disability-adjusted life expectancy (DALE) in this report in 2000, but the name DALE was changed into HALE later on (Mathers *et al.*, 2001).

2006; Evandrou *et al.*, 2014; Zhang and Li, 2015), and that variations in HLE mirror the differences in regional economic development (Liu *et al.*, 2010). Thus, it can be argued that the HLE for a province is likely to be close to that of another country with similar social, economic and demographic conditions. This idea has been applied to analysis on life expectancy (LE). Using estimates for province-level cause-of-death mortality rates by Zhou *et al.* (2016), The Economist (2015) compares provincial-level LE in China with the rest of the world. The comparison shows that in 2013 LE in Shanghai was as high as in Switzerland, while LE in Xinjiang was roughly the same as in Algeria.

Therefore, we argue that by treating each province as a separate "country", we can learn from other countries' experience and predict provincial-level HLE in China. By sampling mortality and morbidity experience from a wide range of countries, we "borrow" information to overcome the problem of not having sufficient data for provincial-level analyses for China. In the next section we develop a multiple regression model that utilizes the predictive powers of factors that drive the changes in HLE. We estimate the model using data from a wide range of countries.

3 A predictive regression model for HLE

There are two purposes of regression modeling: (i) to explain the relationship between dependent and independent variables, or (ii) to make predictions of the dependent variable based on a set of independent variables (Mac Nally, 2000; Shmueli *et al.*, 2010). Our primary interest is to predict HLE using information on LE and observable socio-economic variables, hence we develop a predictive regression model.

3.1 Model specification

In the last two decades, several studies have analyzed which socio-economic variables have a strong influence on LE and HLE (e.g., Banister and Hill, 2004; Liu *et al.*, 2010; Murthy and Okunade, 2014; Babiarz *et al.*, 2015). Banister and Hill (2004) found that the determinants of LE at birth in China during the period 1981–1995 included per capita consumption, the illiteracy rate, the number of doctors, and the share of education and health care expenditures. Liu *et al.* (2010) explore the impact of some additional variables such as modern household utilities and health care infrastructure on provincial-level HLE. However, as pointed out by Jagger (2015), projections of HLE purely based on socio-economic factors are still rare in practice and the failure to include certain important factors could lead to a misunderstanding of future HLE trends.

To overcome this problem and better predict HLE, we also include LE in our model, utilizing the strong positive correlation between LE and HLE which has been found in many studies (e.g., Law and Yip, 2003; Liu *et al.*, 2010). Intuitively, this strong correlation is easy to understand as total LE is the sum of HLE and "lost" healthy life years due to disability. Moreover, socio-economic factors that affect LE will also have an impact on HLE (Jagger, 2015). Therefore, rather than performing regression on HLE itself, we model the ratio of HLE to LE instead.

Let $y_{it} = \text{logit}(\text{HLE}_{it}/\text{LE}_{it})$ where the logit function is defined as:

$$\text{logit}(a) = \ln\left(\frac{a}{1-a}\right), \text{ where } a \in (0,1). \tag{1}$$

The predictive regression model is introduced as follows:

$$y_{it} = \beta_0 + \sum_{k=1}^{K}\sum_{j=1}^{J}\beta_{j,k}x_{it,j}^{k} + \epsilon_{it}, \tag{2}$$

where $i \in [1, N]$ represents country/region and $t \in [1, T]$ represents time. $\beta_{j,k}$ is the coefficient of the jth variable of order k, where K is the highest polynomial order to be considered and J represents the number of explanatory variables in the model. Note that the model selection process described in the following section can set some of these coefficients to zero. ϵ_{it} denotes the error term. We model the logit transformation of the ratio of HLE to LE to ensure that the value of HLE will not exceed the value of LE.

The selection of socio-economic variables in our model is based on the studies mentioned earlier in this section. In addition, we require the selected socio-economic variables to be both available and consistently defined for all countries included in the estimation process as well as the provinces in China. Based on these criteria, we have selected the following five socio-economic variables:

- GDP: gross domestic product per capita (in 1,000 USD)

- Health: public health expenditure as a percentage of GDP
- Education: public education expenditure as a percentage of GDP
- Hospital bed: number of hospital beds per 1,000 people
- Physician: number of physicians per 1,000 people

In addition, we introduce an East-Asia binary indicator variable $D_{EastAsia}$ into the model to capture any distinctive characteristics of East-Asian countries that would affect the estimation of HLE. Several studies have found that there is a certain degree of advantage in Asian mortality experience compared to other ethnic groups (e.g., Elo and Preston, 1997; Acciai *et al.*, 2015). The National Institute on Ageing also found that over the last few decades, the most rapid improvements in LE at birth have occurred in East-Asia (National Institute on Ageing, 2011). In our study, apart from China, other countries included in the East-Asia region are: Cambodia, Indonesia, Japan, South Korea, Laos, Mongolia, Philippines, Thailand and Singapore. We have included these countries because all of them have strong cultural, historical or ethnolinguistics ties with China and in some cases also have significant Chinese minorities.

3.2 Estimation and model selection

The $\beta_{j,k}$ coefficients in the model are estimated by the ordinary least squares (OLS) method. We obtain estimates of these coefficients by minimizing the following sum of squared residuals:

$$\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \beta_0 - \sum_{k=1}^{K}\sum_{j=1}^{J}\beta_{j,k}x_{it,j}^{k})^2 \tag{3}$$

To derive the matrix form expressions of these OLS estimators and their standard errors, we further define the following terms:

- $\tilde{Y} = (Y_1', \ldots, Y_N')'$, where $Y_i = (y_{i1}, \ldots, y_{iT})'$ for $i = 1, 2, \ldots, N$.
- $\tilde{X}$=$(X_1', X_2', \ldots, X_N')'$ with X_i= $\begin{pmatrix} 1 & x_{i1,1} & \ldots & x_{i1,J} & \ldots & x_{i1,1}^K & \ldots & x_{i1,J}^K \\ \vdots & \vdots & \ddots & \vdots & \ldots & \vdots & \ddots & \vdots \\ 1 & x_{iT,1} & \ldots & x_{iT,J} & \ldots & x_{iT,1}^K & \ldots & x_{iT,J}^K \end{pmatrix}$ for $i = 1, 2, \ldots, N$.
- $\beta = (\beta_0, \beta_{1,1}, \ldots, \beta_{J,1}, \ldots, \beta_{1,K}, \ldots, \beta_{J,K})'$.

Therefore, we can re-express Equation (3) in a matrix form as:

$$(\tilde{Y} - \tilde{X}\beta)'(\tilde{Y} - \tilde{X}\beta), \tag{4}$$

and the OLS estimators are thus expressed as:

$$\hat{\beta} = (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{Y}. \tag{5}$$

We define λ to be the logistic function. The point estimate for HLE is then given by:

$$\widehat{\mathrm{HLE}} = \mathrm{LE} \times \lambda(\tilde{X}\hat{\beta}), \tag{6}$$

where $\lambda(b) = \frac{e^b}{1+e^b}$, and $b \in R$. To construct prediction intervals for HLE, we use the delta method described in Greene (2003) for approximating moments of the parameters in the model. We define $f(\beta)$ to be the matrix of partial derivatives of β coefficients:

$$f(\beta) = \begin{pmatrix} \frac{\partial\lambda(\tilde{X}\beta)}{\partial\beta_0} \\ \frac{\partial\lambda(\tilde{X}\beta)}{\partial\beta_{1,1}} \\ \vdots \\ \frac{\partial\lambda(\tilde{X}\beta)}{\partial\beta_{J,K}} \end{pmatrix} \tag{7}$$

The $100 \times (1-\alpha)\%$ prediction interval is then given by:

$$\widehat{\mathrm{HLE}} \pm t_{(1-\frac{\alpha}{2}, n-p)} \times \sqrt{\mathrm{LE}^2 s^2 + \mathrm{LE}^2[s^2 f(\beta)'(\tilde{X}\tilde{X}')^{-1} f(\beta)]}, \tag{8}$$

where n is the sample size and p is the number of parameters in the model. $t_{(1-\frac{\alpha}{2}, n-p)}$ is the two-sided critical value at the significance level α from the Student's t-distribution with $(n-p)$ degrees of freedom. We define $s^2 = (\tilde{Y} - \tilde{X}\hat{\beta})'(\tilde{Y} - \tilde{X}\hat{\beta})/(n-p)$.

As mentioned in Section 3.1, some of the coefficients in Equation (2) can be set to zero as we only want to include those variables that have high predictive power for the dependent variable. We therefore adopt a model selection process that reflects the predictive purpose of the proposed model. We need to consider the trade-off between goodness of fit and parsimony of the model as a non-parsimonious model can lead to poor prediction results (Tibshirani, 1996). Obviously, a "better" fit can often be obtained by introducing more model terms, but not all of the terms will have high predictive power and thus sometimes the forecasting results can be worsened (Härdle, 1990; Mac Nally, 2000).

We identify the optimal model using the following selection process:
(1) We start with a polynomial order of $K = 1$ for all variables in Equation (2) and compare all possible model specifications based on the Bayesian information criterion (BIC). The BIC is a widely used model selection criteria due to its many desirable properties (Schwarz, 1978). We select the model with the lowest BIC value.
(2) We use the Ramsey Regression Equation Specification Error Test (RESET) to test for mis-specification of the selected model (Ramsey, 1969). If the model is mis-specified, we move on to step (3).
(3) We repeat steps (1) and (2) for the next higher polynomial order until the Ramsey RESET test is passed.

4 Data

4.1 Data used for estimation

The proposed model is estimated using data from a wide range of countries worldwide. We obtained data on LE and HLE at birth for 188 countries in 1990, 2005 and 2013 from the GBD report (Murray *et al.*, 2015), for both males and females. The explanatory variables including GDP per capita (in 1,000 USD), public health expenditure as a percentage of GDP, public education expenditure as a percentage of GDP, the number of hospital beds per 1,000 people and the number of physicians per 1,000 people were collected from two main sources: the World Bank (2017) and the OECD (2017). For each explanatory variable, when the World Bank data for a given country in a given year was missing, we used data from the OECD instead. If the observation was not available from either data source, a nearest neighbor interpolation with a two-year bandwidth was used to approximate the value based on information from the two data sources. Otherwise, the observation was treated as missing. Our final sample has 222 observations from 139 countries that have completed data in one or more years of 1990, 2005 and 2013.

4.2 Data used for model validation

Before applying the estimated model to predict provincial-level HLE for China, we want to make sure that it not only fits the data well, but also provides reliable out-of-sample predictions for HLE. Two sets of validation are conducted in Section 5. First, we compare the model-predicted male and female HLE for 128 countries in 2010 with the corresponding published figures in the GBD Study (Salomon *et al.*, 2013). Information on all socio-economic variables included in the model was collected from the World Bank (2017) and the OECD (2017). We note that the 2010 data was not used for estimating the model[2].

Secondly, we assess the performance of the model based on its out-of-sample prediction accuracy for Taiwan in the years 2005, 2010 and 2013. Even though information on HLE and LE for Taiwan can be obtained from the GBD Study, Taiwan is not included in the estimation dataset as its socio-economic variables are not available from either the World Bank or the OECD. However, due to its strong historical and cultural links to China, the accuracy of HLE predictions for Taiwan provides us a credible indication of whether the model is suitable for predicting HLE for Chinese provinces. Therefore, we compute the HLE estimates for Taiwan and compare them with published figures. Explanatory variables included in the model are obtained from three sources: World Data Atlas (2017), National Statistics Republic of China (Taiwan) (2017) and Chowdhury (2007).

4.3 Data used for prediction of provincial-level HLE

Using the estimated model, we predict HLE for 31 provincial-level regions in China in 2015. The National Bureau of Statistics of China publishes provincial-level male and female LE based on census data every ten years. We first estimate the provincial-level LEs in 2015 using linear extrapolation from the published provincial-level LEs in 2000 and 2010. We adjusted the extrapolated values to ensure that the national-level LE computed based on our estimates is consistent with the national-level LE figure published in the GBD study (Kassebaum *et al.*, 2016). The adjustment requires data on the population size for each province, which was obtained from the China 1% Population Sample Census 2015 (National Bureau of Statistics of China,

[2]The 2010 HLE estimates were published in the GBD report by (Salomon *et al.*, 2013) which used slightly different prevalence measures as in Murray *et al.* (2015). Therefore, the 2010 data were not included in the estimation process.

2017a). A detailed description on the adjustment method is provided in the appendix. The provincial-level socio-economic data are obtained from two main sources: the National Bureau of Statistics of China (2017b) and China Data Online (2017)[3].

5 Results

5.1 The estimated model

Following the model selection procedure described in Section 3.2, we identify the optimal models using the BIC measure and the Ramsey RESET test. The results are shown in Table 1. When we only include first-order terms ($K = 1$), the selected models for both male and female HLE fail the Ramsey RESET test at the 5% level of significance, suggesting the occurrence of possible model mis-specifications. When quadratic terms are allowed in the model ($K = 2$), both optimal models pass the Ramsey RESET test and have lower BIC values indicating a better model fit. Therefore, these are our final selected models.

Table 1: Model selection and Ramsey RESET test results

K	No. of parameters	BIC	RESET test p-value	RESET test outcome
		Male		
1	5	-307.54	0.0034	Fail
2	7	-315.12	0.1715	Pass
		Female		
1	5	-451.55	0.0104	Fail
2	6	-479.09	0.0752	Pass

Note: Each line represents the selected model for a given polynomial order K of the explanatory variables. Models are selected using the BIC. No. of parameters is the number of parameters in the model including the intercept.

The detailed estimation results for the final selected models are shown in Table 2. For both genders, the selected variables are jointly and individually significant at the 5% level. Male HLE can be best predicted by a combination of GDP, Health, Education, Hospital bed, Hospital bed-squared and the East-Asia binary indicator. The HLE model for females shares similar variables with the male model, but does not include Health and Education. However, GDP-squared was included instead. The R^2 statistics show that both models explain the variations in HLE well.

[3]China Data Online is an online database for China studies produced by the China Data Center at the University of Michigan in collaboration with All China Market Research Co., Ltd.

Table 2: Estimation results

Dependent variable:	Logit (HLE/LE)	
	Male	Female
Intercept	1.853**	1.795**
	(0.025)	(0.012)
GDP	-0.002**	-0.006**
	(0.001)	(0.001)
$GDP^2 (\times 10^2)$		0.005**
		(0.001)
Health	-0.013*	
	(0.006)	
Education	0.018**	
	(0.005)	
Hospital bed	0.042*	0.030**
	(0.006)	(0.004)
Hospital bed^2	-0.002**	-0.002**
	(0.000)	(0.000)
East Asia	0.111**	0.134**
	(0.032)	(0.021)
F-stat	16.623**	30.894**
R^2	0.984	0.994
Sample size	222	222

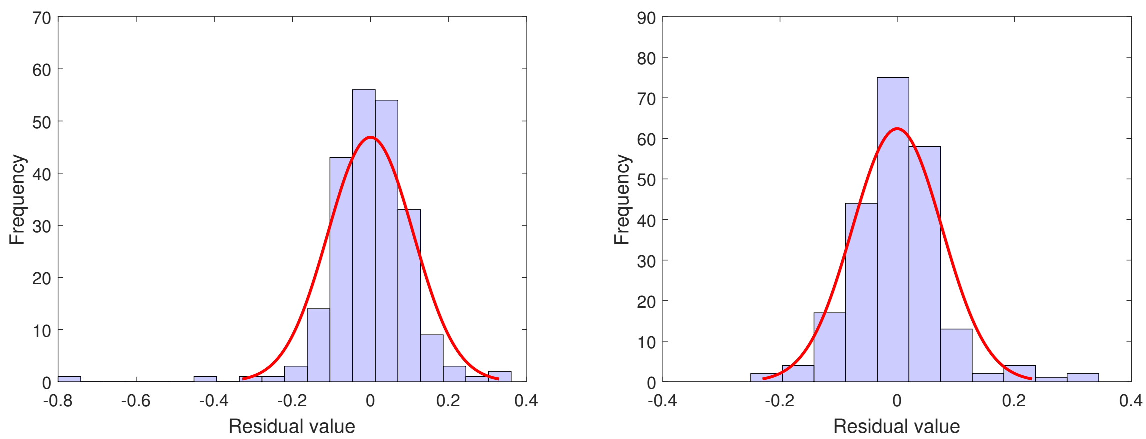
Note: The response variable in both columns is the logit transformation of the ratio of HLE to LE. Robust standard errors (Huber-White) are shown in parentheses. F-stat is the test statistics for the joint significance of all independent variables. * and ** indicate significance at the 5% and 1% level, respectively. R^2 represents the percentage of variations in HLE explained by the model.

We also plot the residuals from the estimated models in Figure 1. The figure shows that both models produce unbiased estimates of the dependent variable and the residuals are approximately normally distributed. In addition, it can be seen that the residual volatility for the male model is slightly higher than for the female model.

Figure 1: Residuals for the models in Table 2.

(a) Males

(b) Females



5.2 Out-of-sample prediction performance

We first assess the prediction performance of the estimated model by comparing the model-predicted HLE with the published HLE for 128 countries in 2010. Table 3 shows the results for both males and females. 113 out of 128 countries in this comparison are originally included in the estimation process. The remaining 15 countries are therefore counted as out-of-sample countries. For males, the model-predicted HLE falls within the confidence interval of the published HLE for 97% of the in-sample countries and 87% of the out-of-sample countries. We find similar results for the female model with only two countries' model-predicted HLE falling outside the published confidence interval. Overall, the results show that the proposed models capture the cross-sectional variations in HLE well. We find a high level of prediction accuracy for both the in-sample countries and out-of-sample countries.

Table 3: Prediction performance test results for HLE in 128 countries in 2010

	In-sample countries	Out-of-sample countries	Total
	Male		
Inside published CI	110	13	123
Outside of published CI	3	2	5
% Inside CI	97%	87%	96%
	Female		
Inside published CI	111	15	126
Outside of published CI	2	0	2
% Inside CI	98%	100%	98%

Note: We compare model-predicted HLEs with HLEs and corresponding confidence intervals (in parentheses) published in Salomon *et al.* (2013). In-sample countries are those which are included in the data set for the estimation of the model. Out-of-sample countries are those which are not included in the estimation.

In addition, we want to test whether the model is suitable to predict the provincial-level HLE and is able to capture the development of HLE over time. Table 4 compares the model-predicted HLE for Taiwan with the published figures for both genders in the years 2005, 2010 and 2013. We find that the model-predicted HLE for males increased from 66.51 years in 2005 to 68.14 years in 2013. These numbers are very close to the published HLE, which increased from 66.68 to 68.11 years over the same time period. Similarly, the model-predicted HLE for females increases in line with the published figures. On average, the model-predicted HLE deviates from the published HLE by less than 0.5 years. These results show that the estimated model provides very accurate predictions of HLE for Taiwan over the period from 2005 to 2013. Because Taiwan has strong historical and cultural links with China, this validation result gives us additional confidence to apply the model to predict HLE for the provincial-level units in China.

Table 4: Prediction performance test results for HLE in Taiwan

Year	Male		Female	
	Predicted HLE	Published HLE	Predicted HLE	Published HLE
2005	66.51	66.68 (64.37–68.71)	70.87	70.41 (67.46–73.07)
2010	67.73	67.20 (65.20–68.90)	71.83	72.00 (69.80–73.80)
2013	68.14	68.11 (65.59–70.23)	72.15	71.66 (68.51–74.46)

Note: We compare model-predicted HLEs with HLEs and corresponding prediction intervals (parentheses) published in Salomon *et al.* (2013).

5.3 Provincial-level HLE for China

Using the estimated models, we predict the HLE for 31 provincial-level regions in China in 2015. Tables 5 and 6 show the model-predicted HLE and the associated prediction intervals for males and females. We can see from the two tables that there is a large degree of heterogeneity in HLE across China for both males and females. Beijing has the highest HLE for both genders: it is 70.53 and 73.78 years for males and females, respectively. Conversely, Yunnan has the lowest HLE for males (60.44 years), while Tibet has the lowest HLE for females (63.37 years). For both genders, HLE varies by about 10 years across China. The prediction intervals for HLE computed by the model are around 3.7–4.0 years for males and 2.7–2.9 years for females.

Tables 5 and 6 also show the corresponding LE and number of years spent in disability for each province. Overall, we can see that provinces with high LE will also tend to have high HLE. This confirms the strong positive correlation between the two variables. Years spent in disability are calculated as the difference between LE and HLE. It is interesting to note that males and females in provinces that have high LEs and HLEs also spend more years in disability. In the case of males, Tianjin has the highest number of years in disability (8.58 years). On the other hand, the years in disability is only 6.14 years for Qinghai which has the third lowest HLE across all provinces. It is well-documented that, on average, females have longer lifespans than males (see, for example, Katz *et al.*, 1983; Oeppen and Vaupel, 2002; Barford *et al.*, 2006). The results in Tables 5 and 6 confirm this finding and also show that the HLEs of females are generally higher than those of males by roughly 2 to 3 years. Females also spend more years in disability. For females, the years in disability range between 10.43 and 8.57 years; while for males, the corresponding range is only 8.58 to 6.14 years. This gender difference in disability years has also been found in several previous studies (see, for example, Arber and Ginn, 1993; Murtagh and Hubert, 2004; Van Oyen *et al.*, 2013).

Table 5: Predicted HLE for provincial-level units in China in 2015, males

Rank	Province	LE	Predicted HLE	Prediction Interval		Years in disability
				Lower bound	Upper bound	
1	Beijing	78.97	70.53	68.54	72.52	8.45
2	Tianjin	78.20	69.63	67.65	71.61	8.58
3	Shanghai	77.92	69.54	67.57	71.52	8.38
4	Zhejiang	75.89	67.77	65.82	69.72	8.12
5	Jiangsu	74.84	66.80	64.87	68.74	8.03
6	Jilin	74.28	66.46	64.53	68.38	7.83
7	Liaoning	74.22	66.37	64.44	68.30	7.85
8	Guangdong	74.40	66.30	64.37	68.22	8.10
9	Heilongjiang	73.88	66.20	64.28	68.11	7.69
10	Shandong	74.02	66.16	64.24	68.08	7.86
11	Shaanxi	73.60	65.97	64.05	67.89	7.63
12	Chongqing	73.62	65.91	64.00	67.83	7.71
13	Fujian	73.56	65.63	63.72	67.55	7.92
14	Hainan	73.28	65.62	63.70	67.53	7.66
15	Shanxi	73.14	65.55	63.64	67.46	7.58
16	Hubei	73.18	65.50	63.59	67.41	7.67
17	Hunan	72.71	65.13	63.22	67.03	7.59
18	Sichuan	72.57	65.09	63.19	66.99	7.48
19	Inner Mongolia	72.73	65.01	63.10	66.91	7.73
20	Anhui	72.70	64.98	63.07	66.88	7.73
21	Jiangxi	72.55	64.92	63.01	66.82	7.63
22	Hebei	72.53	64.84	62.94	66.74	7.69
23	Guangxi	71.95	64.40	62.50	66.29	7.55
24	Xinjiang	71.30	64.27	62.37	66.16	7.04
25	Henan	71.76	64.21	62.32	66.10	7.55
26	Gansu	71.36	64.15	62.25	66.04	7.21
27	Ningxia	71.45	64.02	62.13	65.91	7.43
28	Guizhou	69.25	62.34	60.48	64.21	6.91
29	Qinghai	68.77	61.79	59.94	63.65	6.98
30	Tibet	67.14	61.00	59.08	62.93	6.14
31	Yunnan	67.37	60.44	58.60	62.27	6.94

Note: The table is ranked by the value of predicted HLEs from the highest to the lowest.

We did not interpret the estimated coefficients in our models as the model is used for predictive rather than explanatory purposes. However, when investigating the relationship between the estimated HLE and GDP per capita on its own, we find that the patterns of variation in HLE are very similar to those in economic development across regions. For example, the Pearson correlation coefficient between male HLE and GPD per capita is 0.83. For females, the link between economic development and HLE is also positive, but less strong with the correlation coefficient being 0.58. These findings are consistent with the results by Liu *et al.* (2010), who also found that the variations in HLE mirror the differences in regional economic development in China.

Table 6: Predicted HLE for provincial-level units in China in 2015, females

Rank	Province	LE	Predicted HLE	Prediction Interval		Years in disability
				Lower bound	Upper bound	
1	Beijing	84.21	73.78	72.33	75.22	10.43
2	Shanghai	83.54	73.20	71.76	74.64	10.34
3	Hainan	82.29	72.41	70.98	73.84	9.88
4	Tianjin	82.31	71.96	70.53	73.39	10.35
5	Guangxi	81.60	71.88	70.46	73.30	9.72
6	Zhejiang	81.61	71.65	70.23	73.08	9.96
7	Heilongjiang	80.79	71.26	69.85	72.67	9.53
8	Chongqing	80.86	71.26	69.85	72.67	9.60
9	Jiangxi	80.83	71.17	69.76	72.58	9.66
10	Guangdong	80.99	71.05	69.64	72.47	9.94
11	Liaoning	80.51	70.89	69.48	72.30	9.62
12	Shandong	80.36	70.69	69.28	72.10	9.68
13	Fujian	80.33	70.54	69.13	71.95	9.79
14	Jilin	80.05	70.49	69.08	71.90	9.56
15	Hunan	79.89	70.47	69.07	71.88	9.42
16	Anhui	79.87	70.33	68.93	71.73	9.54
17	Sichuan	79.60	70.26	68.86	71.67	9.33
18	Inner Mongolia	79.92	70.25	68.85	71.66	9.66
19	Jiangsu	80.01	70.21	68.80	71.62	9.80
20	Henan	79.59	70.16	68.76	71.56	9.43
21	Hubei	79.42	70.00	68.60	71.41	9.42
22	Shaanxi	79.37	69.95	68.55	71.35	9.42
23	Shanxi	79.04	69.69	68.29	71.09	9.35
24	Hebei	78.83	69.42	68.02	70.81	9.41
25	Xinjiang	77.63	68.54	67.15	69.92	9.09
26	Ningxia	77.55	68.32	66.94	69.71	9.23
27	Guizhou	77.29	68.24	66.86	69.62	9.05
28	Gansu	76.87	67.82	66.45	69.20	9.05
29	Yunnan	75.11	66.27	64.91	67.62	8.85
30	Qinghai	74.17	65.43	64.08	66.79	8.73
31	Tibet	71.94	63.37	62.05	64.70	8.57

Note: The table is ranked by the value of predicted HLEs from the highest to the lowest.

In Figures 2 and 3 we show two heat maps to further explore the geographic distribution of HLE across China. The figures show that HLE generally decreases from eastern to western China, with Beijing, Tianjing, Shanghai, Zhejiang and Hainan having the highest HLEs. The HLE in provinces along China's east coast is above 65 years for males and above 70 years for females, which are comparable to the values for European developed countries published in the GBD Study (Kassebaum *et al.*, 2016). Provinces in central China have moderate levels of HLE, ranging from 63 to 67 years for males and 68 to 71 years for females. Western China generally has lower levels of HLE compared to central and eastern China. In particular, Tibet, Qinghai and Yunnan in the southwest of China have the lowest HLE figures, with male and female HLE lower than 62 and 67 years, respectively. These numbers are comparable to the HLE in African developing countries such as Egypt.

Figure 2: Provincial HLE for males.

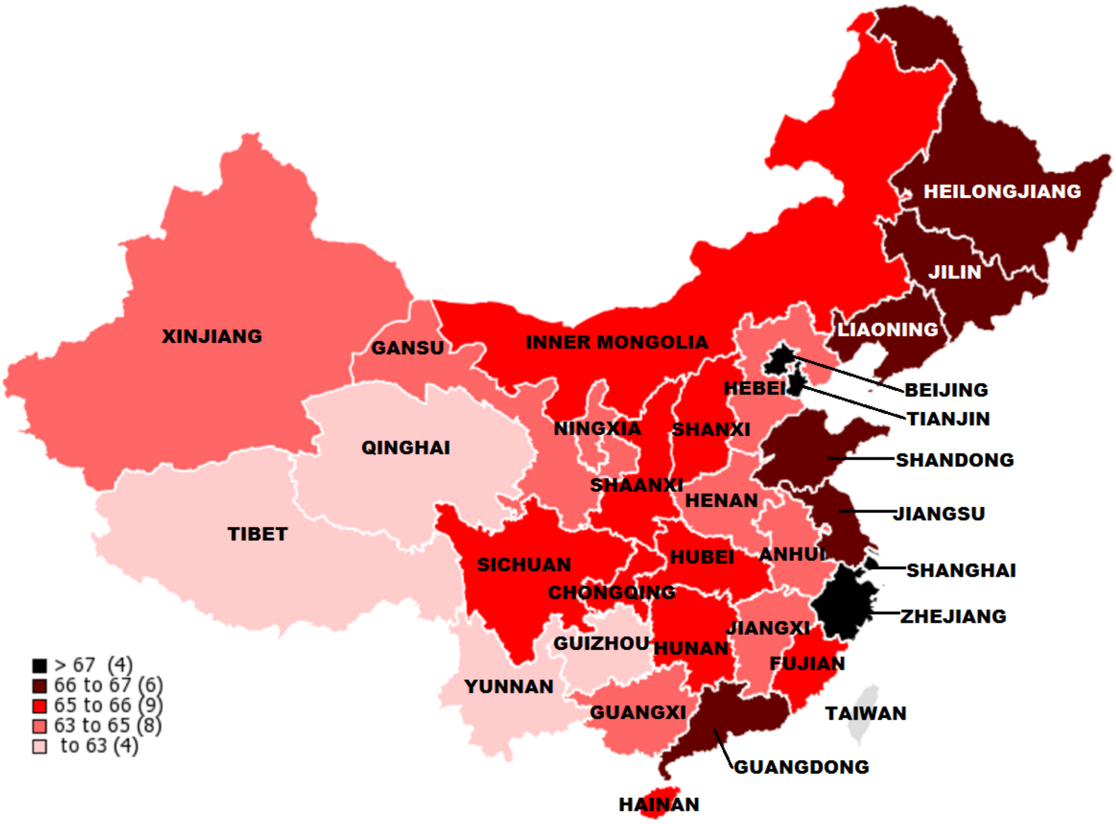
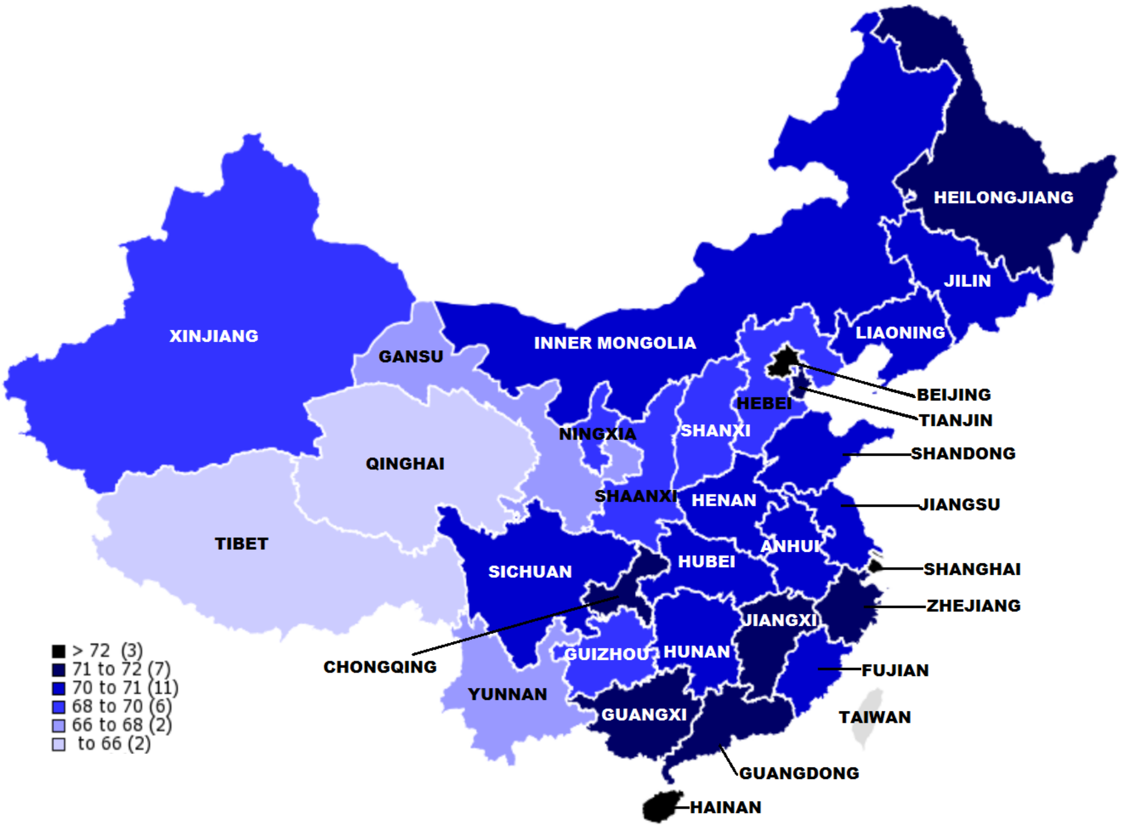


Figure 3: Provincial HLE for females.



Liu *et al.* (2010) estimate provincial-level HLEs for China using the Sullivan method. They compute disability-free life expectancy at age 60, which is different from the HLE measure we adopted in this study. Nevertheless, the regional patterns of HLE in 2006 based on their estimates are still very similar with our results shown in Figures 2 and 3. Moreover, Liu *et al.* (2010) also report a gap of about 10 years between the highest and the lowest provincial-level HLE estimates. These similarities suggest that (i) our new predictive regression model can capture regional variations in HLE across China adequately and (ii) health inequalities in China have persisted over the period 2006-2015.

6 Discussion and conclusions

In this paper we propose a new method to estimate HLE for different subregions within a country and apply the model to provincial-level administrative units in China. Differing from the standard Sullivan method, our model does not require age-specific morbidity and mortality data. Instead, we develop a predictive multiple regression model based on socio-economic variables including GDP per capita, public health expenditure, public education expenditure, number of hospital beds and number of physicians. Information on LE is also used to assist with the prediction of HLE. The proposed model is estimated using data from a wide range of countries globally. We contribute to the understanding of health inequalities in China by providing the most up-to-date estimates of HLE at birth for 31 provincial-level units in 2015. Our results show that the inequalities in health outcomes across Chinese provinces still persist. For both males and females, the difference between the highest and the lowest provincial-level HLEs is approximately 10 years. We also find regional clusterings of HLEs with high HLEs mainly in eastern China and low HLEs mainly in the southwestern part of China.

Since the proposed predictive regression model does not require detailed age-specific mortality and morbidity rates, the model can also be applied to estimate HLE for other countries in years where morbidity information is not available. Furthermore, as the methods for forecasting life expectancy (Majer *et al.*, 2013; Wong and Tsui, 2015) and macro-level social-economic variables (see, e.g., Litterman, 1986) are readily available, the model can also be used to project future HLE.

Our results can inform the design of public policies in China. The Chinese government is planning to gradually increase the pension eligibility age for urban employees to age 65 for both men and women. The current pension eligibility age is 60 for males and 50 to 55 for females. Previous research has shown that health is an important factor in individuals' retirement decisions in China (Giles *et al.*, 2015). Our HLE estimates indicate that there is potential for increased labor force participation at higher ages. However, we also find that there are 12 provinces with a male HLE of under 65 years, suggesting that in these provinces many men may not be able to work until age 65 for health reasons.

Another challenge China is currently facing is the development of its health care and long-term care system for the elderly. There are several ongoing pilot projects to develop formal social long-term care services in China (see, for example, Lu *et al.*, 2015, 2017). Our study provides estimates of both HLE and the number of years spent in disability for each province. These results are useful to assess the differences in regional demand for health care and long-term care services. Since China will maintain a very high level of demand for health related services in the following decades, the government is also actively seeking private-market solutions to share the burden of health costs. Our study can contribute to the development of private-market retirement financial products including private health insurance, private long-term care insurance and home equity release products such as reverse mortgages.

Appendix

Linear extrapolation was used to compute LE in 2015 for the 31 provincial-level regions included in this study. We used the LE figures published by the National Bureau of Statistics of China in 2000 and 2010. The formula used to extrapolate the 2015 HLE for province i is given by:

$$\mathrm{LE}_{2015,i} = \mathrm{LE}_{2010,i} + \frac{1}{2}(\mathrm{LE}_{2010,i} - \mathrm{LE}_{2000,i}). \tag{9}$$

We then compute a constant scaling factor c for both male and female populations such that

$$\text{Published national level } \mathrm{LE}_{2015} = \sum_{i=1}^{31} c \times w_{2015,i} \times \mathrm{LE}_{2015,i}\ , \tag{10}$$

where we have

$$w_{2015,i} = \frac{\text{Population size}_{2015,i}}{\text{National population}_{2015}}. \tag{11}$$

The estimated constant scaling factor $\hat{c}$ was 0.9840 for males and 0.9988 for females.

Finally, we obtain $\mathrm{LE}^*_{2015,i}$ which is the adjusted LE for province i in the year 2015 as

$$\mathrm{LE}^*_{2015,i} = \hat{c} \times \mathrm{LE}_{2005,i}. \tag{12}$$

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