**Transition Probability Matrices and Forecasting of Long-Term Care Demand**

Xiaodong Cui *
Nanjing Xiaozhuang University
Nanjing, China

**Abstract**—To provide an actuarial basis for the long-term care security system, and to research health state transition probability and the size of population with long-term care demand. Methods- Based on actuarial theory to construct transition probability matrices, adopt the Markov process with transition intensities as piecewise constants to forecast the size of population needing long-term care. Innovation-The transition probability matrices based on the actuarial theory can avoid the subjectivity of variable selection in the common regression analysis method; the piecewise constant Markov method can overcome the defect that the Markov time invariant hypothesis is not in conformity with the reality of health state varying with age.

Results- In the coming decade, the number of disabled population in China will be increased to 1.5 times the current number, and the number of female disabled population will be around 2 times that of male disabled population; the women who are advanced in age and poor in health are the main group with a demand for long-term care in the future. Significance—This study is beneficial to the accumulation of basic information for the construction of China’s long-term care security system for the elderly, thereby, providing a decision basis for the government to develop an aging strategy.

**Keywords**—Long-term Care; State Transition Matrix; Markov Process; Piecewise Constant Probability

I. **INTRODUCTION AND LITERATURE REVIEW**

This Long-term care means “providing care or other support services for people under disability within a long period”[1]. Due to illness, disability, function decline or other reasons, the aged population becomes the main group with a demand for long-term care. According to the sixth national census data, the ratio of the elderly aged 60 and above who cannot care for themselves in China is nearly 3% (Lin Bao, 2015) [1]. Moreover, with the increase of life expectancy and the decline of fertility level, China’s aging population shows a high-speed and advanced-age trend. The aging rate is averagely increased by 0.34 every year from 2010 to 2025, and the ratio of the aged population is increased from 8.9% to 14%, which reflects a serious aging problem (Zheng Wei, 2014) [2]. In the meantime, aging is associated with family miniaturization. According to the sixth national census data, the average number of members in each family is 3.10 in China, and the average number of members in each urban family is only 2.87. However, the number of members in each urban family was 3.50 in 1990 (Hu Hongwei, 2015) [3]. Family miniaturization causes the weakening of traditional family-based elderly support function and the aging of population, and the combination of the two brings a severe challenge to China’s pension system. As China’s current social welfare and social security system are unable to solve the long-term care problem for most elderly people, the establishment of a long-term care security system is an inevitable choice for coping with aging. So far, China’s long-term care security system is in the exploration stage. This study is aimed to research the actuarial basis of the long-term care security system, i.e., transition probability of health state and the population size required for long-term care.

The forecasting methods of the demand for long-term care are divided into macro scenario simulation forecasting and micro simulation data forecasting. Macro scenario simulation means constructing scenarios by setting different parameters of key factors, then speculating the demands for long-term care in different scenarios. There is a difference in the factor selection and setting of different documents. Comas-Herrera (2006) [4] took the lead in applying a simulation method to forecast the demand for long-term care in four European countries, and found that the demand for long-term care is highly sensitive to living standard, health state, nursing cost, as well as the availability of family or friend care; Comas-Herrera (2008) [5] used the data provided by the actuarial department to forecast the demand for long-term care from 2005 to 2031 in his research on the UK, and found that the selection of such parameters as marital state, family members’ dwelling state and degree of disability has a great influence on the forecasting; Costa-Font (2008) [6] constructed the PSSRU model, and forecasted the population with a demand for long-term care in the future by simulating the number of population under different circumstances and multiplying it by the ratio of the current population under long-term care to the total population; Zhu Minglai et al. (2009) [7] and Zeng Yi et al. (2010) [8] speculated the number of the elderly needing long-term care based on the same method. The results of macro simulation greatly rely on the selection and setting of parameters. Comas-Herrera (2012) [9] used the analytic hierarchy process to verify this conclusion by selecting different factors.

Micro simulation forecasting is based on micro survey data to follow up the evolution track of health state of the elderly. The key of this method is the construction of the transition probability matrix and the application of Markov process. Rickayzen (2002) [10] took the lead in applying Markov process to the forecasting of demand for long-term care, and divided the calculation of the transition probability matrix into
two parts. First, the ratio of population under each state at the beginning of the period to the total population is used as the base period probability; then the base period probability is adjusted according to the variation trend of health state so as to calculate the transition probabilities of the forecast period in sequence. Hare (2009) [11] obtained the transition probability by regression model based on the factors influencing the demand for long-term care, and his research data came from medical departments and individual surveys. Based on the same regression method, Chahed et al. (2011) [12] used the health state transition data of patients in London from 2008 to 2011, and Peng et al. (2010) [13] utilized the health state survey data of China’s aged population to construct the transition probability matrix, and forecasted the elderly people’s demand for long-term care under Markov time invariant hypothesis; In the research by Peng Rong (2009) [14] in China, the transition probability is borrowed from the national long-term care survey & research results of the USA; Huang Feng (2012) [15] and Hu Hongwei (2015) [3] respectively established a mortality probability model and a health state transition model through logit and ordinal logit regression models, and assumed that the health transition probability matrix is unchanged during the forecasting when applying the Markov process method.

In the comparison between the two forecasting methods, as macro scenario simulation is restricted by the selection and hypothesis of numerous key factors, the forecasting model based on micro data is relatively dominant in the case of data available [16]. The “Chinese Longitudinal Healthy Longevity Survey” (CLHLS) program conducted by the Center for Healthy Aging and Development Studies, Peking University, has made some progress for the domestic research based on micro forecasting, but still has some room for improvement in application. First, in the aspect of the construction of the transition probability matrix, the direct borrowing of the overseas transition probability or the simple period-on-period method has low precision, which cannot meet the requirement of the insurance system [15]. Second, the multiple regression model construction method is a more common method. But the complicated, diversified and multidimensional characteristics of changes in health state add diversity and subjectivity to the selection of explanatory variables in the regression model. The last, in the aspect of the time invariant hypothesis of Markov process, the nature of time invariant hypothesis is that the transition intensity is an invariant constant, and the transition probability is only related to time interval, but unrelated to its time point. This hypothesis is convenient for the expression of the transition probability function. However, the changes in health state are related to age. People of different ages have different changes in health, i.e., the transition probability is related to the time point. Thus, the time invariant hypothesis of Markov process is improper.

In this regard, based on the micro simulation forecasting method, the changes in health state before and after the observation period of samples in the CLHLS survey program are tracked in this paper, and the actuarial method is adopted to construct the transition probability matrix to avoid the subjectivity of variable selection in regression analysis; the Markov process method with transition intensities as piecewise constants and matrix multiplication by age is adopted to forecast the number of long-term care population, and to overcome the defect of Markov time invariant hypothesis not in conformity with the reality. Considering that the micro simulation forecasting loses the reliability of medium and long-term forecast due to model refinement and forecast precision advantages, this paper is focused on forecasting the demand size of ten-year long-term care.

II. DATA AND MODEL

A. Data Source and Definition of Health State

Two types of data are mainly used in this study. The first type of data came from the CLHLS (2011-2014). This survey was carried out in 22 provinces of China, and related data were collected by means of questionnaire interviews in each household. Hundreds of scholars at home and abroad have registered for free use of CLHLS, the data quality of which is good and has been widely accepted by the academic circles. In this study, the elderly people aged 65 and above in the tracking survey samples were the objects of study. After the observed value lacking key information and the data unavailable for follow-up tracking were removed, the number of effective samples were 15,964, and the male to female ratio was 0.93:1. The CLHLS data were used to calculate the transition probability matrix and reckon the ratio of the population in each health state to the total population in the base period. The second type of data came from the China’s Demographic Yearbook of 2016, used as the number of population in the base period.

In this study, the definition of nursing state is subject to the ADLs (activities of daily living) independence criterion widely used in the academic circles. According to the criterion, in case that a person needs help from others in one or more of the six items reflecting the activities of daily living of the elderly, it is defined as self-care disability; if a person has three or more daily activity disorders, such person is deemed to need long-term care. Besides, considering that one of the objectives of this study is providing a basis for the long-term care security system, cognitive impairment is also defined as self-care disability so as to enable the definition of long-term care state to be consistent with the long-term care security system. In CLHLS, The simple scale about the respondents’ health state covers 24 questions and 30 points in total. The scoring method is used in CLHLS, wherein, the ability to complete an activity or a correct answer will add 1 point for the respondent.

In this study, health state is divided into four types, respectively, 1 health, 2 health impairment, 3 dysfunction and 4 death. The definition of health state is based on three indexes, namely, ADLs, IADLs and cognitive ability. If a person has no disorder in none of the three, such person is deemed to in a health state 1. If a person has three or more than three daily activity disorders, i.e., the ADLs score is larger or equal to 3 points or the cognitive function score is below 16 points (30 points in total), the person is deemed to be in the state of dysfunction 3, namely, the state of needing long-term care. The complementary state is deemed as health impairment state, i.e., a certain disorder exists, but does not reach the state 2 of needing long-term care.
B. Mechanism Analysis of Markov Process

With the help of the multi-state model in long-term health insurance actuarial science, a four-state probability transition model is adopted pursuant to the above definition in this paper.

1) Markov process.

A Markov process refers to a set of random variables \( \{X(t), t \in T\} \) relying on the variable parameter \( t \), the set of \( T \) all possible values of the variable parameter \( t \) is known as a parameter space, and the value \( S \) of \( X(t) \) constitutes the state space of a stochastic process. If it is known that the time \( t \) system is under a state condition, when the state of the time \( t (t > t) \) is unrelated to the previous state of the time \( t \), this process is a Markov process.

In this paper, the four-state probability transition model can be regarded as a Markov process with \( T \) discrete and \( S \) discrete. \( T \) is a set of ages, and \( S \) represents four health states. In other words, the transition probability of health states is only related to the state before transition, which can be expressed as the following mathematical symbol:

\[
T_x^j = p[s(x+i) = j | S(x) = i]; j = 1, 2, 3, 4; i = 1, 2, 3 \tag{1}
\]

2) Transition probability matrix.

States 1, 2 and 3 are transferable states while state 4 is the absorption state. The transition probability meets the Chapman-Kolmogorov equation:

\[
P^k_{i,j} = \sum P^k_{i,l} P^l_{l,j} \quad i = 1, 2, 3; k = 1, 2, 3; j = 1, 2, 3, 4 \tag{2}
\]

For different \( x \), i.e., different ages in this paper, with different transition probabilities, the transition probabilities of different ages are expressed as matrices. The one-step transition probability is denoted as matrix \( P(t) \); the \( t \)-step transition probability matrix is \( P(t) \).

\[
P(t) = P(m)(1) \cdot P(m+1)(1) \ldots P(m+t-1)(1) \tag{3}
\]

Where, \( P^{m+t-1}(1) \) represents the one-step transition matrix at time \( m+t-1 \).

When the transition probability is only related to the initial state \( i \) and the arrival state \( j \), but unrelated to the initial time \( x \), the Markov chain has a stationary transition probability, also known as time-homogeneous transition probability.

Transition intensity represents the instantaneous transition of state, which is denoted as:

\[
\mu^i(t) = \lim_{\Delta t \to 0} \frac{P^i(t + \Delta t) - P^i(t)}{\Delta t} = \frac{p^i(t)}{P^i(t)} \tag{4}
\]

From this, the relation between transition intensity and transition probability can be inferred:

\[
P_x^t = e^{\int^t_0 \mu^i(s)ds} \tag{5}
\]

When the transition intensity is the constant \( \mu \):

\[
P_x^t = e^{\mu t} \tag{6}
\]

The nature of the Markov process time invariant hypothesis is that the transition intensity is an invariant constant, i.e., the time interval of state transition is subject to exponential distribution, and the state transition probability is only related to the time interval, but unrelated to the time point. This hypothesis is convenient for the expression of a transition probability function, but is improper in many applications. For example, if we assume that the health state transition probability is time-homogeneous, it means that no matter 60, 70 or 80, as long as the time intervals of transition observed are the same, the health state transition probabilities are the same. In other words, the people aged 60, 70 or 80 have the same changes in health state within the following equal time, which is apparently not in conformity with the reality. Therefore, based on the non-homogeneous characteristic of transition intensity varying with age, the forecasting method with transition intensity as a piecewise constant is adopted so as to maintain the easy controllability of constant transition intensity in this paper. That is to say, a given forecast interval \( (s,t) \) is divided into short intervals. We assume that the transition intensity of each short interval is a constant, but the transition intensities of the \( m \) short intervals are different. In the process of calculating the transition probabilities of \( (s,t) \), the transition intensity of each short interval is calculated first, then the transition probability intensity of this short interval, finally the transition probability matrix of the entire interval.

A ten-year transition probability matrix is forecasted in this paper. It is divided into ten intervals on a yearly basis. We assume that the transition intensity every year is a constant, but the transition intensities in different years are different. Then according to Equation (3), the future ten-year transition probability matrix can be expressed as:

\[
P(0,10) = P^0 P^1 \ldots P^9 \tag{7}
\]

It should be noted that unlike the time invariant hypothesis, \( P^0, P^1 \ldots \) here, i.e., the transition probabilities of all intervals, are unequal to one another. Theoretically, we might track the health state transition of samples every year to obtain ten section matrixes for multiplication, but it is actually infeasible and unnecessary for short and medium-term forecasting. For the section matrix of health transition of each age group obtained by the utilization of samples, dislocation multiplication is applied during forecasting. For the forecasting of the future 10-year health transition probability of people aged \( x \), we assume that each year is a short interval, then we can apply the transition probability of age \( x \) in the section data to the first interval, the transition probability of age \( x+1 \) in the section data to the second interval, the transition probability of age \( x+2 \) in the section data to the third interval. It should be also noted that \( P^0, P^1, \ldots \) are one-year transition probabilities, and the three-year transition probabilities are

\[
As long-term care often results from chronic and long-term diseases, it is reasonable to set the health transition probability within one year as a constant (the explanation comes from Health Insurance, exam book required by the China Association of Actuaries).

\[
In the short to medium-term, the macro-environment has an insignificant impact on health (Zeng Yi).
\]

\[\]

\[\]
obtained according to CLHLS survey data from 2011 to 2014. Therefore, the one-year transition intensities and one-year transition probabilities need to be obtained pursuant to Equation (5), and then substituted into Equation (6).

III. FORECASTING RESULTS

A. Three-Year Health State Transition Probability Matrix

As the sample data are three-year tracking survey data, the three-year health state transition probability matrix is calculated first. Table I is the three-year health state transition probability matrix of different ages and genders completed with SPSS software. In the process of sorting data, considering that age and gender are important influencing factors of health state, first, the samples are classified by age and gender. Every five years is an age group (if every age is a group, more accurate results will be obtained, but there will be too many data. Moreover, when there is only a small age difference, the transition probability difference will be insignificant). Each individual of each category is classified as different health state according to the definition standard of health state, then, the health states of individuals in different states at the end of the period are tracked in each category so as to calculate the ratio of the number of people in each state at the end of the period to that at the beginning of the period, which can be counted as the corresponding three-year transition probability.

| Age | State | men | | | | women | | | |
|-----|-------|-----|-----|-----|-----|-----|-----|-----|-----|
|     |       | 1   | 2   | 3   | 4   | 1   | 2   | 3   | 4   |
| 65-69| 1     | 0.6754 | 0.2403 | 0.0237 | 0.0606 | 0.5333 | 0.3767 | 0.0500 | 0.0400 |
|      | 2     | 0.3869 | 0.4201 | 0.1003 | 0.0927 | 0.3768 | 0.4589 | 0.1063 | 0.0580 |
|      | 3     | 0.2010 | 0.4000 | 0.2490 | 0.1500 | 0.1923 | 0.4231 | 0.2692 | 0.1154 |
| 70-74| 1     | 0.5279 | 0.2817 | 0.0711 | 0.1193 | 0.5233 | 0.2746 | 0.1451 | 0.0570 |
|      | 2     | 0.3948 | 0.3542 | 0.1107 | 0.1403 | 0.2073 | 0.5793 | 0.1189 | 0.0945 |
|      | 3     | 0.2364 | 0.2545 | 0.1455 | 0.3636 | 0.1837 | 0.1429 | 0.4286 | 0.2448 |
| 75-79| 1     | 0.3202 | 0.3900 | 0.0969 | 0.1929 | 0.3006 | 0.4247 | 0.1561 | 0.1186 |
|      | 2     | 0.1968 | 0.4124 | 0.1860 | 0.2049 | 0.1654 | 0.3780 | 0.2703 | 0.1863 |
|      | 3     | 0.0625 | 0.2813 | 0.2188 | 0.4375 | 0.0645 | 0.2903 | 0.3710 | 0.2742 |
| 80-84| 1     | 0.3196 | 0.3144 | 0.1443 | 0.2217 | 0.1900 | 0.4364 | 0.2216 | 0.1520 |
|      | 2     | 0.1119 | 0.3776 | 0.2005 | 0.3100 | 0.0502 | 0.3480 | 0.3542 | 0.2476 |
|      | 3     | 0.0518 | 0.2798 | 0.2642 | 0.4042 | 0.0190 | 0.2531 | 0.3742 | 0.3537 |
| 85-89| 1     | 0.0755 | 0.4854 | 0.1946 | 0.2445 | 0.0456 | 0.4154 | 0.3051 | 0.2339 |
|      | 2     | 0.0363 | 0.3189 | 0.2104 | 0.4344 | 0.0297 | 0.3051 | 0.3729 | 0.2923 |
|      | 3     | 0.0178 | 0.1684 | 0.2579 | 0.5559 | 0.0117 | 0.1202 | 0.3806 | 0.4875 |
| 90-94| 1     | 0.0339 | 0.3266 | 0.2358 | 0.4037 | 0.0385 | 0.1923 | 0.3077 | 0.4615 |
|      | 2     | 0.0149 | 0.1983 | 0.2593 | 0.5275 | 0.0045 | 0.2123 | 0.4234 | 0.3598 |
|      | 3     | 0.0101 | 0.0911 | 0.2376 | 0.6612 | 0.0058 | 0.0764 | 0.3299 | 0.5880 |
| 95+  | 1     | 0.0833 | 0.2500 | 0.2500 | 0.4167 | 0.0156 | 0.0940 | 0.4005 | 0.4899 |
|      | 2     | 0.0185 | 0.1806 | 0.2454 | 0.5556 | 0.0107 | 0.1584 | 0.3083 | 0.5226 |
|      | 3     | 0.0033 | 0.0542 | 0.1921 | 0.7504 | 0.0011 | 0.0272 | 0.2484 | 0.7233 |
As shown in Table I, the samples are classified into different groups by age and gender, and each group is divided into different state. The data at the intersection represents the corresponding state transition probability. For instance, among the elderly men aged 65-69 who are in State 1 (i.e., health) at the beginning of the period, the ratio of the elderly men remaining in State 1 at the end of the period is 0.6574; the ratio of the elderly men in State 2 is 0.2403; the ratio of the elderly men in State 3 is 0.0237; the ratio of the elderly men in State 4 (i.e., death) is 0.0606. The remaining data have the same meaning.

B. One-Year Transition Probability Matrix

The three-year transition probability matrix \( P(3) \) is obtained in Table I. To calculate one-year transition probabilities, we may conduct a staged time invariant hypothesis, i.e., assuming that the transition probability intensity of each category within the three years is a constant to reversely calculate \( P(1) \) according to Equation (3). In this paper, mathematic programming is utilized to calculate the transition intensity, then to calculate the one-year transition probability matrix. Due to limited space, the matrix is not listed in the text.

C. Ten-Year Transition Probability Matrix of Piecewise Constant Transition Intensities

In accordance with the one-year transition probability matrix, the transition probability in each category and different state after any period can be calculated via Equation (5). As each age group is on a five-year basis, with a forecast period of ten years, the forecast period is divided into two parts. The transition probability of the age group is applied in the first 5 years, and the transition probability of the next age group is applied in the last 5 years. For instance, for the forecasting of the ten-year transition probability matrix of people aged 65-69, the transition probability every year in the first five years is the one-year transition probability of the age group of 65-69; then 5 years later, the one-year transition probability matrix of the age group of 65-69 is adopted in the last 5 years\(^5\). In the meantime, it is assumed that the transition probability matrix every year in the five years meets time homogeneity. \( P_{65-69}(1) \) represents the one-year transition probability of the age group of 60-64; \( P_{70-74}(1) \) represents the one-year transition probability of the age group of 65-69. Then, the ten-year transition probability of the age group of 65-69 is \( P_{65-69}(10) = (P_{65-69}(1))^5 \times (P_{70-74}(1))^5 \). The calculation methods of the remaining groups are the same. The people aged 95+ have a fairly low survival rate, so it is assumed that they are in State 4. In this way, the ten-year transition probability matrix of each group is obtained by means of programming calculation\(^6\).

D. Forecasting of Population Size

Based on the demographic structure data of China’s Demographic Yearbook of 2017, the number of different heath state population in the base period is calculated. The health state population vector of each age group in the base period multiplied by the corresponding ten-year transition probability matrix is the number of population in each state ten years later, as shown in the table below. The datum 153,640 in the table shows that among the men at the age of 65-69, the number of healthy population is 153,460 ten years later; the number of population with health impairment is 103,189; the number of population with a dysfunction (with a demand for long-term care) is 31,241; the number of deaths is 136,966. The rest are similar. The original age group of 95+ enters the age group of 105+ ten years later. It is presumed that they are all in the death state, so they are not included in the table II.

| Age  | men       |     | women     |     |
|------|-----------|-----|-----------|-----|
|      | 1         | 2   | 3         | 4   | 1  | 2   | 3   | 4   |
| 65-69| 153,640   | 103,189 | 31,241 | 136,966 | 121,572  | 141,976  | 65,526  | 96,963  |
| 70-74| 39,185    | 68,672 | 28,866 | 139,877 | 36,383   | 77,365   | 56,975   | 116,042 |
| 75-79| 14,666    | 43,875 | 20,616 | 126,460 | 66,028   | 39,805   | 43,519   | 125,691 |
| 80-84| 1,357     | 11,512 | 9,377  | 89,480  | 11,186   | 1,2059   | 22,368   | 10,5921 |
| 85-89| 118       | 1,309 | 2,259  | 41,160  | 1,07      | 2,082    | 6,431    | 58,291  |
| 90+  | 14        | 128   | 266    | 1,1431  | 10        | 164      | 804      | 20,959  |

The data in the table show that the number of healthy old men is more than that of women in the same age group. Moreover, the number of female deaths is more than that of male deaths before the age of 80-84, because the population size of old men in the later period is reduced, which indicates that men have a health advantage and a survival disadvantage. Seen from the age distribution of disabled population size, the number of old men and women shows a phenomenon of increasing first and decreasing later, and the number of disabled elderly in the age group of 65-69 is the largest.

E. Comparison of disabled population size before and after the ten-year period.

Fig.1 and Fig.2 respectively provide the population size comparison diagram of disabled men before and after the ten-year period, as well as the population size comparison diagram of disabled women before and after the ten-year period. The

\(^5\) If 1 age unit is a group, this hypothesis will not exist.

\(^6\) The matrix is not listed in the paper if have any need, please contact with the author.
two figures show the changes in the number of disabled population within ten years. A comparison of the same age before and after a ten-year period is made. In the process of data processing, as the first age group of samples is 65-69, corresponding to 75-79 ten years later. The rest can be compared in a similar fashion. The three age groups of 85-89, 90-94 and 95+ will enter the 95+ age group ten years later, so the sum of the three group data is compared with the data of the 95+ age group. Seen from the figures, compared to the number of disabled population in the base period, the number of both men and women in all age groups is increased to different extent, wherein, the number of disabled population in the age group of 75-80 is increased significantly; the number of male population is 1.5 times the number in the base period; the number of female disabled population is 1.57 times the number in the base period; the total number of disabled population is 1.53 times the number in the base period. According to Huang Feng’s research results, if it is assumed that the growth rate is unchanged, the number of disabled women is 2.0 times the number in the base period after the ten-year period. Seen from the age characteristics of the disabled population changes, the disabled population from the age group of 75-80 to the age group of 80-85 shows a progressive increase, reaches the maximum change in the age group of 80-85, and begins showing a downtrend at the age of 85+. Fig.7 depicts a gender contrast of the number of disabled population. Seen from the figure, the number of disabled old women in all age groups is more than that of disabled old men, and the total number of disabled women is 2.06 times that of disabled men.

![Fig. 1. Comparison of the Number of Disabled Men](image1)

![Fig. 2. Comparison of the Number of Disabled](image2)

According to Huang Feng’s research results, if it is assumed that the growth rate is unchanged, the number of disabled women is 2.0 times the number in the base period after the ten-year period (i.e., 2026 in this study); the number of disabled men is basically stable, and the total number of disabled population is 1.57 times the number in the base period. Lin Bao measured and calculated that the disabled population shows an annual growth rate of 3% before 2032, so the estimated number of disabled population in 2026 is 1.35 times the current number according to the ratio.

### II. SUMMARY AND CONCLUSIONS

In this paper, the survey data of CLHLS from 2011 to 2014 are utilized to investigate the dynamic evolution process of the health state of the elderly. Based on the Markov theory, tracking survey data are used to construct probability transition matrixes in this paper. Considering the age characteristics of changes in health states, the piecewise constant Markov process method is adopted to forecast the population size of different states in the future. According to the research results: the changes in health have a significant difference in gender and age. Compared to men, old women have a significant survival advantage; compared to women, old men have a health advantage. The superposition of the two enables the number of disabled women of different ages to be around 2 times the number of disabled men in 2026, and the difference reaches the maximum value in the age group of 70-80. The mortality risk and the health risk are increased with the growth of age and the worsening of the initial health state. As a result, the people who are in poor health initially have a bigger possibility of needing long-term care.

Population aging is a global yet irreversible phenomenon. As China has the largest number of aged population in the world, accompanied by miniaturized and hollow family size, the long-term care for the aged population not only adds a financial burden to families, but also forms a huge recession aging debt of a country in the future. Boosting the long-term security system for the elderly is not only the huge progress in aging and social security undertakings made by a country, but also an inevitable strategic choice for a country to cope with population aging. This study contributes to the understanding and recognition of the natural law of body function changes of the elderly, helps policymakers to plan and prepare medical and nursing services required by the elderly, and is beneficial to the accumulation of basic information for the construction of China’s long-term care security system for the elderly, thereby, providing a decision basis for the government to develop an aging strategy.

### REFERENCES

[1] Lin Bao. An Analysis on the Status and Trend of Old Population without Self-care Ability in China [J]. Population & Economics, 2015(4): 77-84. (In Chinese)

[2] Zheng Wei, Lin Shanjun, Chen Kai. Characteristics and Trend of Population Aging in China and Its Potential Impact on Economic Growth [J]. The Journal of Quantitative & Technical Economics, 2014(8): 3-38. (In Chinese)

[3] Hu Hongwei. Estimation and Prediction of Demand of Chinese Elderly Long-term Care Service [J]. Chinese Journal of Population Science, 2015(3): 79-89. (In Chinese)

[4] Comas-Herrera A, Wittenberg R, Costa-Font J. Future long-term care expenditure in Germany, Spain, Italy, and the United Kingdom [J]. Ageing Society, 2006 (2): 285-302.

[5] Comas-Herrera A, Wittenberg R. Cognitive impairment in older people: future demand for long-term care services and the associated costs [J]. Int J Geriatric Psychiatry, 2007(10): 1025-1037

[6] Costa-Font, Wittenberg R. Projecting long-term care expenditure in four European Union member states: the influence of demographic scenarios [J]. Soc Indic Res, 2008 (2): 303–321
[7] Zhu Minglai. The Analysis of Demand for Long-term Care and its Insurance System Constructing in China [J]. Chinese Journal of Health Policy [J], 2009(7):32-38. (In Chinese)

[8] Zeng Yi, Chen Huashuai, Wang Zhengliang. Analysis on Trends of Future Home-based Care Needs. (In Chinese), and Costs for Elderly in China [J]. Economic Research Journal, 2012(10):134-149.

[9] Comas-Herrera A, Northey S, Wittenberg R. Future costs of dementia-related long-term care: exploring future scenarios [J]. Int Psychogeriatric, 2012(1):20–30

[10] Rickayzen B, Walsh D. A multi-state model of disability for the UK: implications for need for long term care for the elderly [J]. Br Actuar J, 2002(2):341–393

[11] Hare WL, Alimadad A, Dodd H. A deterministic model of home and community care client counts in British Columbia [J]. Health Care Manag Sci, 2009(1):80–98.

[12] Chahed S, Demir E, Chaussealet T J. Measuring and modelling occupancy time in NHS continuing Healthcare [J]. BMC Health Res, 2011(11):163-178.

[13] Peng R, Ling L, Qun H. Self-rated health status transition and long-term care need of the oldest Chinese [J]. Health Policy, 2010(2):259–266. (In Chinese)

[14] Peng Rong. Analysis of Senior Population Nursing Needs Based on Markov Model [J], Statistics & Information Forum, 2009(3):77-79. (In Chinese)

[15] Huang Feng, Wu Chunjie. A Study of Long-Term-Care Demand of the Elderly in China: Based on Multistate Transition Model [J], Economic Research Journal, 2012(2):119-130. (In Chinese)

[16] Philip Worrall, Thierry J. A structured review of long-term care demand modelling [J]. Health Care Manag Sci [J]. 2015(18):173–194.