Defining and Modeling Long Term Care Statuses

By

Chi-Tao (Elise) Wu, BS

A dissertation submitted in partial fulfillment of

the requirements for the degree of

Doctor of Philosophy

(Industrial and System Engineering)

at the

UNIVERSITY OF WISCONSIN-MADISON

2013

Date of final oral examination: 05/14/2013

The dissertation is approved by the following members of the Final Oral Committee:

Vicki M. Bier, Professor, Industrial and System Engineering
David J. Vanness, Associate Professor, Population Health Science
Edward W. Frees, Professor, Actuarial Science, Risk Management and Insurance
Thomas C. DeLeire, Professor, Public Affairs and Economics
David R. Zimmerman, Professor, Industrial and System Engineering
James M. Robinson, Director, Center for Health System Research Analysis

Acknowledgement

I would never have been able to finish my dissertation without the guidance of my committee members, help from friends, and support from my family.

I would like to express my deepest gratitude to my mentor/advisor, Dr. Jim Robinson, for his excellent guidance, caring, patience, and providing me with an excellent atmosphere for doing research. I would like to thank Dr.Bier, who patiently corrected my writing and provided valuable feedbacks on modeling skills and methodology. I would also like to thank Dr. Vanness, Dr. Fress, and Dr. Zimmerman for guiding my research and helping me to develop my background in economics, population health science, and industrial engineering. Special thanks goes to Dr. DeLeire, who was willing to participate in my final defense committee at the last moment.

I would like to thank Sarah Lin, who as a good friend, was always willing to help and give her best suggestions. It would have been a lonely journey without her. Many thanks to Dr. Xiao Zhang, Dr. Chia Pu, and other workers in the CHSRA for helping me finish this wonderful journey. My research would not have been possible without their helps.

I would also like to thank my sister, Amber Wu. She was always supporting me and encouraging me with her best wishes. Without her unconditional support, I would not have strength to move forward.

Finally, I would like to thank my best friend, Santosh Shedbalkar. He was always there cheering me up and stood by me through the good times and bad.

Abstract

An understanding of individuals' health status transitions is essential for policymakers, Long Term Care (LTC) managed care organizations, care recipients, and the general public. From the payer's perspective, an individual's LTC status is based on total LTC cost, and the LTC program capitation rate set by state government for individuals is the most suitable estimation for total LTC cost, because capitation rates is the total amount per Medicaid enrollee that the state government pays to the managed LTC care plan monthly. Individuals' LTC status (LTCS) is defined by their monthly capitation rate level. This research addresses the ability to predict future capitation rate level (LTCS) given current capitation rate level (LTCS) among Wisconsin Medicaid managed LTC program enrollees.

The impact of gender, age, and living setting on future LTCS is demonstrated by applying maximum likelihood multinomial logistic regression technique on future LTCS. For building a parsimonious model, the relationships between current and future are modeled instead than absolute future LTCS. A transition model for living situation is developed to collaborate with the capitation rate level transition model. The internal and external validities are confirmed by an additional dataset and published studies.

The developed comprehensive model is used to conduct analytical and simulated projections for two different hypothetical MCOs. The expected results are very similar between the two MCOs, even though the MCO size is significantly different. Yet, the variations for the small MCO are larger than the variations for the big MCO. The results support the proposition that measuring MCO performance needs to consider different perspectives.

Identifying minimal numbers of variables and proposing the parsimonious transition parametric form to predict future capitation rate level are valuable, because it makes the developed model more portable to other states. It proposes possible quality of care indicators for MCOs and detailed information on expected outcomes, and possible ways to improve quality of care and also increase profit for MCO level. Comparing the actual and expected transition rates within and between MCOs provides valuable information regarding quality measurement since it demonstrates variations caused by characteristics of MCOs better than unadjusted, internal quality measurements.

Table of Contents

Chapter 1. Background

The demand for long term care (LTC) service is skyrocketing as the population ages, and LTC has become a crucial issue in the United States. The U.S. Census Bureau has projected that there will be 46 million elderly aged 65 years and over in 2015, and 88.5 million over 65 years old in 2050 [1]. The rapidly increasing elderly population will dramatically affect the U.S. health care delivery system, including LTC financing, the workforce of LTC providers, and the availability of LTC settings such as institutional facilities and home health services.

In 2011, LTC services expenditure was $210.9 billion, as estimated by the Center for Medicare & Medicaid Services (CMS). The LTC services cost estimated by CMS excludes medical and nursing services that are needed to manage the underlying health conditions that lead to frailty or disability. Although Medicare is designed for the elderly, it only covers limited LTC service expenditures from skilled nursing facilities (SNFs) and home health programs concentrating on short-term rehabilitative therapy. As noted in Figure 1-1, Medicaid is the main payer for LTC services expenditures. The CMS estimated that approximately two-thirds of LTC expenditures in 2011 were financed by Medicaid.

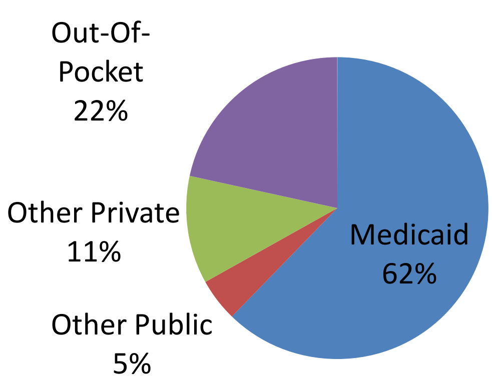

Figure 1-1: Percentage Shares of Spending on LTC for the Elderly in 2011

The trends in the age structure of the population and the growth of LTC expenditures have already presented state Medicaid programs with significant challenges in managing the increasing demand of LTC needs.[2–5] Wisconsin Family Care is an example of a Medicaid-managed LTC program, which is the target population in this dissertation, and managing the Family Care program is a significant challenge for the Wisconsin state government. Advanced budget and care providers capacity planning is beneficial for both state government and managed care organization (MCO) administrators. Additionally, evaluating the performance of LTC MCOs adequately and accurately can improve the quality of LTC paid for by Wisconsin Medicaid. Thus, a comprehensive understanding of the individual LTC recipient's LTC status, which is highly correlated with LTC cost, is required.

Chapter 2. **Conceptual Research Framework**

This dissertation has four main components: characteristics of the target population, LTC status (LTCS), LTC services received, and LTC cost. The details of each component are shown in Figure 2-1 and discussed below. In order to manage an LTC program, an understanding of the characteristics of the target population is necessary. Characteristics of the target population (later referred to as indicators) can be categorized into two types: (1) characteristics that represent an individual's functional ability to perform basic daily tasks such as activities of daily living (ADL)[I] and instrumental activities of daily living (IADL)[II] and (2) characteristics that represent the level of health-related services (HRS)[III] required by an individual such as the frequency of need for tube feeding or diagnosis. Diagnosis represents an individual's medical condition such as Alzheimer's disease, and the HRSs are the results of medical conditions. For example, individual may need to undergo dialysis twice a week (HRS) due to renal failure (diagnosis). Characteristics of the target population are assessed by WI-LTC-Functional Screen (WI-LTC-FS), which is a tool that state government uses to determine individuals' eligibility for the Family Care program. WI-LTC-FS will be discussed in detail in chapter 2.3.

LTC status includes both disability/functional status and medical status. Individuals' functional characteristics are commonly used to define disability/functional status, and indicators of HRS utilization are used to define medical status. The spectrum of LTC services is broad, and includes both skilled medical services and unskilled functional/cognitive support services for those who need assistance due to chronic illness or physical or mental impairments. To elaborate,

[I] ADLs are six routine activities that people tend to do everyday: eating, bathing, dressing, toileting, transferring, and continence.
[II] IADLs are the activities that people tend to do while living independently in the community: housework, medication management, money management, shopping, using the telephone, and transportation. These activities require a higher cognitive level than ADLs do.
[III] HRSs are technical skilled nursing tasks performed by skilled medical personnel.

skilled medical services such as dialysis or tube feeding are provided by registered nurses or licensed practical nurses, while certified nursing aides or personnel with no medical skills training can provide unskilled LTC services such as dressing and bathing. More attention is being paid to LTC issues because of the high demand for LTC services and the challenge of public LTC financing.[6–8] Therefore, the last component of this dissertation is LTC cost, which can be categorized into unskilled and skilled LTC service cost. Each type of LTC cost corresponds to the type of LTC services received.

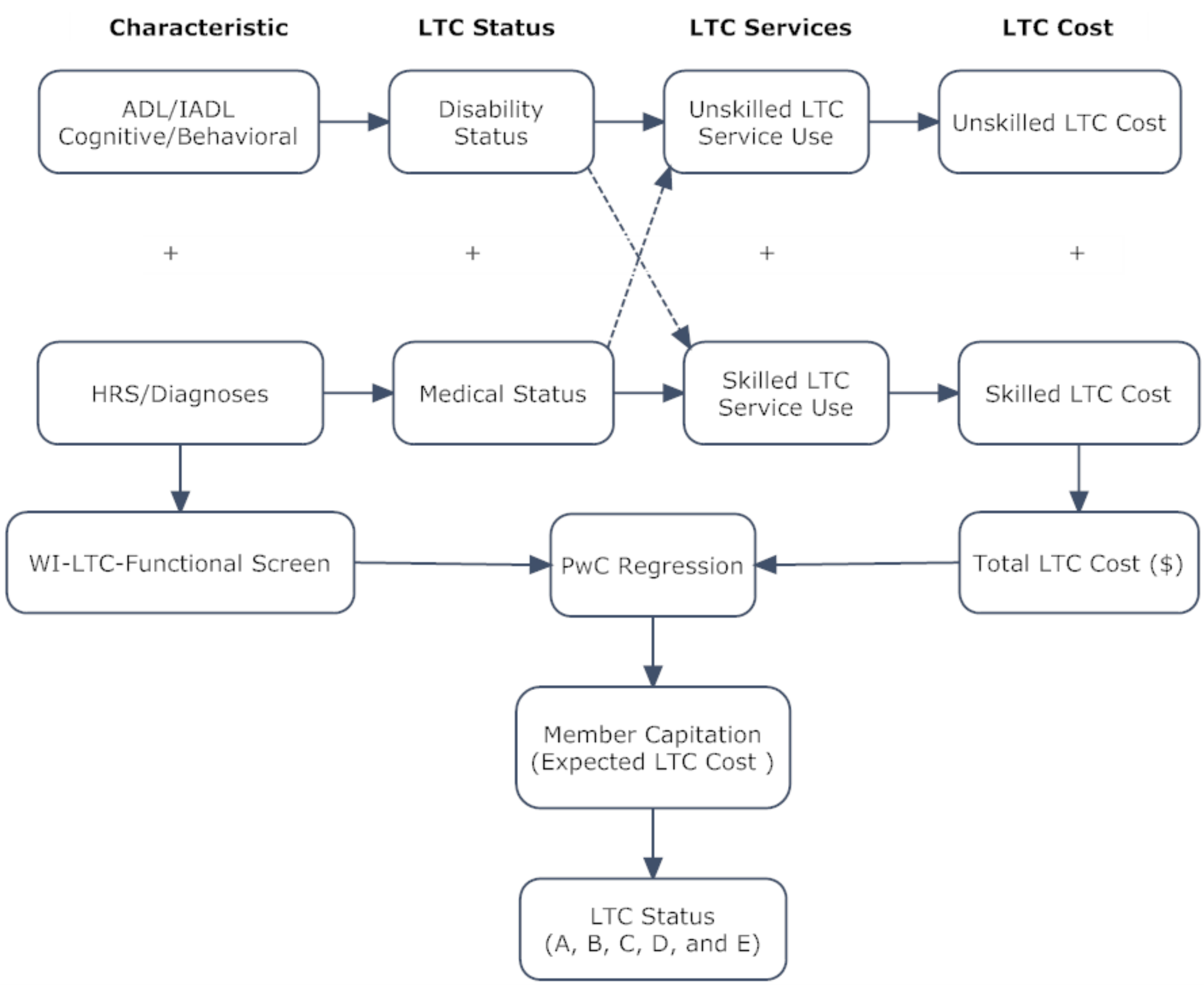

Figure 2-1: Research Concept Flow

Using ADLs and IADLs to estimate LTC cost is common; however, it is questionable whether this approach can really capture total LTC costs. While disability status models defined by ADL and IADL have proven useful in studying the demand for LTC services,[9,10] we note that disability status measures only an individual's ability to perform basic daily tasks, so it can be used to explain only the need for unskilled LTC services. Therefore, we believe that it is necessary to use data on medical status to estimate the need for skilled LTC services. The details of disability status will be discussed in chapter 2.1. Additionally, the need for intensive skilled LTC services does not have an absolute positive relationship with the need for unskilled LTC services. For example, an individual may have no problem performing ADLs and IADLs but need dialysis services provided by an RN twice a week. Thus this skilled LTC service cost will not be reflected by disability status.

Several well-known microsimulation models have been used to predict future LTC demand and costs, such as the dynamic simulation of income model (DYNASIM), developed by the Urban Institute,[11] and the long-term care financing model (LTCFM) developed by the Brookings/ICF.[12] The details of current existing models will be discussed in chapter 2.2.

Since the National Academy on an Aging Society (2000) indicated that approximately 40% of the elderly have at least some functional limitations related to either ADLs or IADLs, these models typically examine changes or transitions over time in "disability status" or "functional status," usually based on a combination of ADL and IADL data, in longitudinal studies of aging. Although current disability status has a primary relationship with future disability status, a secondary relationship with future medical status also exists. Additionally, current medical status has not only a primary relationship with future medical status, but also a secondary relationship with future disability status. Therefore, using a definition of LTCS that includes both disability status and medical status can capture the most comprehensive characteristics for individuals and corresponding LTC services received at various cost levels. An expanded understanding of individual LTCS that incorporates characteristics directly related to the need for skilled LTC, such as diagnoses and needed medical procedures, would be a valuable extension of models considered to date, and would improve federal and state governments' ability to budget and prepare for the future demands of both functional and medical services on the part of the Medicaid LTC population[13,14].

Three reasons explain why this research predicts capitation level rather than actual LTC cost. First, we do not have access to MCO encounter data that could be used to calculate individuals' actual LTC cost. Meanwhile, we do have access to LTC-FS data used to calculate member-level capitation rate. Second, actual member-level LTC cost vary about expected levels due to random, temporary changes in the member's situation. Third, the regression-based capitation level for each member is designed to remove this noise so that we can observe and model trends in costs associated with more persistent member LTC needs. Thus, Medicaid enrollees' capitation rates are the most reasonable basis for estimating expected average total LTC services costs from the payer's perspective, including both skilled and unskilled LTC services cost for the Medicaid population examined by this research. Capitation rates refer to the total amount per Medicaid enrollee that the state government pays to the managed care plan monthly. The expected capitation rate regression formula is constructed by Pricewaterhouse Coopers (PwC) and published by the Wisconsin state government as discussed in chapter 2.4.

Improving the PwC regression formula is not the goal of this dissertation. Rather, the focus of this dissertation is on enhancing the ability to predict an individual's capitation rate for the next year (Y_{t+1}) given the current capitation rate (Y_t) and identify additional explanatory variables (X_t) such as age, gender, medical conditions, and etc that can improve the accuracy of prediction. For example, $Y_{t+1}=\beta_0+\beta_1 Y_t+\beta_2 X_t$ represents that the next year's capitation rate (Y_{t+1}) is estimated by the current capitation rate (Y_t) and other variables (X_t) at time t. Ideally, the future and current capitation rate can be modeled as an continuous variable and adjusted by other explanatory variables, and the coefficients (β) represent the current corresponding variable's impact on future capitation rate.

This dissertation defines an individual's LTCS as the expected capitation rate level for the Medicaid-managed LTC programs. Each member's capitation rate level reflects current medical and functional characteristics from the LTC-FS that are correlated with current skilled and unskilled LTC service costs. Therefore, LTCS in this dissertation reflects both disability status (which is measured by ADL, IADL, and cognitive and behavior impairments) and medical status (which is measured by the need for HRS and diagnoses codes). The ultimate goal of this research is to establish an LTCS transition model that can be used to project the utilization of Medicaid LTC services in the future for populations in need of LTC. In particular, we identify factors that can improve the ability to predict future LTCS. Thus, one overall model can be represented conceptually as follows:

$P\ (LTCS_{t+1}|LTCS_t,\ X_{it})$:

which gives the probability that an individual will be in $LTCS_{t+1}$ at time t+1, given that he or she is in LTCS at time t. The values of the explanatory variables, also previously referred to as indicators, are $X_{1,}\ X_{2,}$.......

$LTCS_t$: Individual capitation level: A, B, C, D, and E at time t

X_{it}: Additional factors such as age and gender at time t

The specific aims of this research will be stated in chapter 2.5.

With a continuous model, it is likely that the transition rates (to higher or lower capitation levels) and the factors that affect these rates will vary based on whether the current level is low, medium or high. That is, in predicting Y(t+1), the interaction between the effects of Y(t) and X(t) is likely to be quite complicated over the entire range of Y(t). So, we break Y(t) into ranges (A, B,…,E) and separately explore the factors that affect migration to other ranges. That is, we initially adopt a series of simpler transition models for each starting range, rather than attempting to build a complex model suitable for the entire range of the starting capitation level. It is left ot future research to determine whether these distinct models for each range can be combined into parsimonious continuous model.

2.1. Disability Status

Disability status is a broad term to describe an individual who is unable to be independent due to physical or psychological impairments. Disability status, either including psychological disability or not, is used widely to predict LTC-related issues. In most studies, the number of limitations for ADLs and IADLs is used for determining the severity of functional disability. The higher the total numbers of limitations for ADLs or IADLs, the more serious the functional disability status.

Table 2-1 summarizes the indicators that are commonly used to measure or represent disability type. As mentioned previously, disability is divided into two types: physical and mental. There are three different measurements to evaluate physical disability and two different measurements for mental disability. Each measurement assesses the individual's ability to perform different tasks independently.

The definition of disability status, which is based on these indicators, varies according to different studies. In general, limitations for IADLs appear to reflect a less severe disability level; therefore, previous researchers did not emphasize the total number of IADLs, instead using a dummy variable to represent the earliest stage of the disability process. As individuals have limitations for ADLs, researchers would only focus on the total number of ADLs to classify the severity of disability level, regardless of IADLs. However, small degrees of difference do exist among previous researchers' methods. For example, instead of analyzing ADLs and IADLs separately, the indexes developed by Rosow and Breslau adopted and combined ADLs and IADLs to determine the severity of disability level (De Leon et al., 1999). In addition, ADLs usually include 6 activities—eating, dressing, bathing, mobility in home, toileting, and transferring— but not all of them happen at the same frequency. Some ADL limitations happen rarely, such as toileting and dressing;[16] thus, these items have been excluded in some studies. According to the National Academy on an Aging Society, the progression of LTC intensity is as follows: independent living, decline in IADLs, decline in ADLs, and institutionalization.[17]

Table 2-1: Type and Description of Health Status Measurement

Disability Type	Measurement	Tasks
Physical	• ADLs	• Bathing • Dressing • Eating • Mobility in home • Toileting • Transferring
	• IADLs	• House work • Meal preparation • Medication management • Money management • Use of telephone • Transportation
	• Functional Limitation	• Stooping/kneeling • Lifting 10 pounds • Reaching over head • Writing • Walking two or three blocks
Psychological	• Communication and cognition	• Communication • Memory loss • Cognition for daily decision making • Physically resistive to care
	• Behaviors and mental health	• Wandering • Self-injurious behaviors • Offensive or violent behavior toward others • Mental health needs • Substance abuse

In order to elaborate further, the inclusion of cognitive impairment is necessary, as it has a significant impact on disability level.[8,18] In Robinson's and Stallard's studies, cognitive impairment was included in disability status. Chronic cognitive impairment is associated with Alzheimer's disease and dementia, with or without ADL and IADL limitations. Therefore, the early stage of chronic disability is associated strongly with medical acute care due to cognitive impairments and based on the nature of the disability; the need will shift to LTC later.[8]

Table 2-2 summarizes the disability status definitions used by several studies. The number of disability stages varies from study to study, and several studies use additional variables, such as living arrangement, to define status. In general, a higher number of limitations leads to more serious functional disability status. However, many factors have a significant impact on LTC service costs, which are not related to physical functional ability. According to complex correlations between different types of disability, measurements of functional disability, such as ADLs and IADLs, do not cover the full range of the definition of health status.

Table 2-2: Summary of Status Definition Used by Previous Studies

Studies	Status of disability
(Leon et al., 1999)	• Disabled • Not disabled • Dead
(Branch et al., 1984) (Guralnik et al., 2002)	• Independent • Disabled in community • Institutionally disabled • Dead
(Waidmann & Liu, 2000)	• Independent • Physically limited • IADL disabled • ADL disabled • Institutionally disabled
(Manton et al., 2006) (Manton & Soldo, 1992) (Chernew et al., 2005)	• Independent • IADL disabled • 1-2 ADLs disabled • 3-4 ADLs disabled • 5-6 ADLs disabled • Institutionally disabled
(Anderson et al., 1998)	• Independent • IADL disabled only • 1-2 ADLs disabled (moderately) • 2+ ADL disabled (severely)
(Hardy et al., 2005)	• Independent • 1-2 ADLs disabled (mild) • 3-4 ADLs disabled (severe) • Dead
(Mor et al. , 1994)	• Independent • IADL disabled only • 1-2 ADLs disabled • 3+ ADLs disabled
(Stallard, 2011)	• Independent • Mild/moderately disabled • HIPAA ADL only • HIPAA CI only • HIPAA ADL and cognitive impairment, jointly • Dead

(Robinson, 1996)	• Independent • IADL disabled only • 1 ADL disabled, no cognitive impairment • 2ADL disabled, no cognitive impairment • 3+ ADL disabled, no cognitive impairment • <2 ADLs with cognitive impairment

2.2. Current Existing Models

2.2.1. Congressional Budget Office's Long-Term Model (CBOLT)

CBOLT is a microsimulation model of the U.S. population, as well as economic and budget planning. It was initiated in 2000 but has been modified and developed since then. Recently, CBOLT has been adding details on Medicare, Medicaid, and other health care expenditures to the actuarial framework.[19]

The input data used in CBOLT is from the continuous work history sample (CWHS), an administrative dataset housed by the Social Security Administration (SSA) that includes information about each individual's demographic data, Social Security information and earning records. CBOLT also uses data from other sources, such as the Survey of Income and Program Participation (SIPP), the Panel Study of Income Dynamics (PSID), and the Current Population Survey (CPS), to estimate the statistical relationship between individual characteristics that already exist on CBOLT. Those estimates can provide a fundamental recommendation to explain the data that are not available in the CWHS.

There are two main modules in CBOLT: demographics and economics. CBOLT sets a baseline for demographics based on historical data and Social Security trustees' aggregate population projection by age categories, gender, and marital status. Other demographics, such as education level, are imputed by using the survey data mentioned above.[20] There are several assumptions, such as fertility, mortality, immigration, disability incidence and termination rates, and health care cost growth. We will focus on mortality, as well as disability incidence and termination rate, because these two components have a direct relationship with health status.[21] Mortality rates by age and gender match Social Security trustees' projections, but mortality rate also depends on marital status and education;[7] therefore, the CBOLT microsimulation model accounts for differential mortality, which will lead to a more accurate distributional analysis.

CBOLT also implements the incidence rate from Social Security Disability Insurance by age and gender provided by Social Security trustees. Using these data allows researchers to estimate the prevalence of disability and the probability of being a disabled beneficiary by age and gender. Moreover, Topoleski and Manchester[22] have indicated that modeling health status, which relates to work, marital status, fertility, mortality, health care expenditure, and health status transitions, will be required for improving the CBOLT microsimulation model.

The CBOLT model is an effective model to project LTC-related issues. Many policy researchers have used the projection from CBOLT to analyze how economics could affect LTC scenarios.[23–25] CBOLT projected that spending on LTC for the elderly, financed by Medicare, will reach 51 billion dollars in 2020 without inflation, and Medicaid costs will increase to 75 billion dollars in 2020 without inflation.[20] CBOLT can also be used to project Medicare or Medicaid spending on different LTC facilities, such as skilled nursing facilities and home health care. Medicaid's expenditures for home and community-based health care are much smaller than its spending on institutional care facilities;[20] however, home health has been growing rapidly compared to other health sectors since 2007.[24]

In sum, CBOLT is used widely for analyzing the budget distributional impacts caused by Social Security programs and other federal policies and programs.

2.2.2. Dynamic Simulation of Income Model (DYNASIM)

DYNASIM was developed by the Urban Institute in 1970 and DYNASIM2 was established in 1980, focusing on analysis for retirement income issues.[11,26] DYNASIM3 is the most updated dynamic microsimulation model designed to analyze the long-term distribution of retirement and aging-related issues. The Urban Institute claims that DYNASIM3 includes more information on demographics and family income, as well as new household saving and private pension coverage modules, and Social Security and Supplemental Security Income (SSI) calculators.

The input file for DYNASIM3 is based on the Survey of Income and Program Participation (SIPP) panels from 1990 to 1993. Due to the confidentiality of Summary Earning Records (SER) from the Social Security Administration (SSA), which constrained the data collection, the researchers synthesized individual earning histories based on statistically matched SIPP with the Panel Study of Income Dynamics (PSID) from 1968 to 1993. The synthetic earning histories are used only in calculating Social Security benefits for years of work prior to 1992, since the conversion to the 1993 SIPP has provided valuable information on individual and family housing and financial wealth.

DYNASIM3 contains three modules: demographics, economics, and taxes and benefits. There are three components in demographics (i.e., population growth, family formation, and education and health), with two main characteristics related to health (i.e., disability status and institutionalization). As the health-related characteristics will be the focus of this research, the details will be discussed below. DYNASIM3 includes a discrete-time hazard model for disability status using work limitations, a dummy dependent variable, and other explanatory variables established by previous studies, such as age, education, lifetime earning, and marital status.[27] In addition, DYNASIM3 applied to working limitations will predict the number of limitations in ADLs that elderly people might have as a function of their demographics. DYNASIM3 also projects the future living arrangement at age 65 and over, based on a discrete-time event history model.

The applications of the DYNASIM series are broad. Zedlewski and McBride adopted it to analyze the future need for LTC services and the affordability of LTC insurance for the elderly; they predicted that 4.3 million elderly people will live in nursing homes by 2030 and that the expenditures related to nursing homes will reach $189 million in the same year.[28] Numerous previous studies used DYNASIM3 to analyze LTC needs and expenditures related to future retirement outcomes, such as evaluating Social Security reforms.[27,29,30] Assessing the preparedness for baby boomer retirement plans is another application of DYNASIM3.[31–33] Johnson et al. (2007) added an LTC module that was mostly based on analysis of the Health Retirement Study (HRS), a nationally representative longitudinal survey, to DYNASIM3, and it projected that the number of disabled elderly with at least one ADL or IADL limitation will increase to 21 million by 2040. In essence, DYNASIM is a well-known microsimulation model, which is applied to many areas; however, only ADLs and IADLs are used as a health-related indicator, and thus health status may not be fully covered.

2.2.3. Long-Term Care Financing Model (LTCFM)/ Pension and Retirement Income Simulation Model (PRISM)

ICF/ Brookings Institute developed LTCFM to simulate the utilization and financing of both institutional and non-institutional LTC services by the elderly from 1988 to 2025.[26] LTCFM is an extension of PRISM. PRISM was also first developed by ICF/Brookings Institute in 1980, and it simulates future elderly demographics, labor force participation, income, elderly family situations, and assets of the elderly. Using the Monte Carlo method, LTCFM adopted these results launched from PRISM as its population information for simulating disability, admission to LTC facilities, and LTC financing alternatives.[12] There are six subcomponent sections in LTCFM: representative population database; simulate income, labor force activity, family structure, assets in each year in future from modified version of PRISM; simulate disability of the elderly; simulate utilization of LTC services; simulate sources and levels of payment; and analysis tabulation. The first three components establish the population database by using PRISM and the next three components simulate utilization and payment for LTC.

The input file for PRISM is based on the Current Population Survey (CPS) from 1979 as a population database, simulating the onset of disability, the level of disability, and migration within disability by using the estimated probabilities from the National Long Term Care Survey (NLTCS) and National Nursing Home Survey (NNHS) for disability of the elderly. This model also uses NNHS to simulate admission to nursing homes and length of stay in the nursing home. Combining the information collected by Medicare LTC programs with these two surveys allows the model to simulate the utilization of non-institutional facilities, such as home and community-based health care services.

This model categorizes disability status into four levels based on the functional level: (1) having at least one limitation for IADLs; (2) having at least one limitation for ADLs; (3) having two or more limitations for ADLs; and (4) no disability. Subsequently, the model simulates the utilization of nursing homes based on the previous probabilities. The reason this model uses functional status rather than chronic illness status is because even without chronic illness, people may still enter nursing homes due to short-term rehabilitation.[34] Moreover, the LTCFM uses NLTCS to simulate the migration between disability status by age and sex.

The LTCFM can be applied to numerous areas. Because of the characteristics of microsimulation, such as estimating the distributions of services needed throughout individuals' lifetimes, the scope of projection can be expanded. LTCFM not only projects the LTC need of a population at a certain point in time, but also simulates individual LTC need distribution throughout a person's lifetime. Although Medicaid currently covers much less of the cost of community-based or home health programs compared to what it covers for institutional care, LTCFM projected that 69% of people who turned 65 in 2005 will need LTC in their lifetime and 65% of them will receive LTC from home health programs.[35] An additional $26.1 billion, which includes medical and LTC costs, will be incurred when the elderly become more dependent since 1995.[6] Medicaid spending as a share of NHE will increase to 19% by 2045,[36] and adopting private LTC financing options will not change much about this trend.[37]

In 2030, the baby boomers will be a high-risk population for LTC services. LTCFM can be applied to predict their wealth, which has a big impact on their ability to afford LTC services. Although the LTCFM forecasted that the elderly will be wealthier and be able to handle health-related issues in 2030,[38] Knickman and Snell indicated that it will be helpful if the necessary changes in public policy are implemented before most of the baby boomers need LTC services.[4] LTCFM collaborates with PRISM to estimate health care cost across different scenarios, such as policy and economic changes. Level of disability, which only includes functional status, plays an important role within the simulation process; thus, defining health status as including more indicators can improve the results launched by PRISM and also enhance the prediction results from LTCFM.

2.2.4. Future Elderly Model (FEM)

The CMS needs to predict future health expenditures accurately for budget planning, so it contracted with RAND Corporation to develop a microsimulation model called Future Elderly Model (FEM), a demographic–economic model, to forecast future health care expenditure and health status.[39] FEM is the largest and most widely used microsimulation model developed by Dana Goldman et al. FEM includes multidimensional characteristics of health status, such as ADLs, clinical diagnoses, and residency situations (i.e., institutional facilities or home health care).

The base dataset for FEM, the Medicare Current Beneficiary Survey (MCBS), sponsored by the CMS, is defined as “a continuous, multipurpose survey of a nationally representative sample of aged, disabled and institutionalized Medicare beneficiaries” and is the only comprehensive source of information on the health status, health care use and expenditures, health insurance coverage, and socioeconomic and demographic characteristics of the entire spectrum of Medicare beneficiaries.[40] In order to predict cost, capture clinically relevant disease, and supplement the gaps in MCBS and other datasets such as National Health Interview Survey (NHIS), FEM defined health status based on self-reported health conditions and disability.[41] However, the definitions of disability are slightly different between MCBS and NHIS. For example, instead of asking about showering and walking in MCBS, NHIS asks if individuals have difficulty getting around inside the home. These differences caused by the questions using diverse approaches in separate surveys explain the variance in disability rate between the two surveys.

The three main models in FEM are health care cost, health status transitions, and characteristics of new Medicare enrollees. The dependent variable in FEM is total Medicare reimbursements, and the explanatory variables are age, sex, race, education, geography, mortality, physical health, and interactions of these measures. FEM indicated that costs increase rapidly with ADLs, especially with more than three ADL limitations;[41] however, improving the disability rate will not help save Medicare expenditure dramatically in the long run.[42] Additionally, Joyce et al. indicated that the growth of accumulated Medicare cost related to chronic illness is modest due to the shorter life expectancy of those who have severe chronic illnesses.[43] Although improving disability rate will not facilitate significant Medicare savings, Cutler used FEM to extract potential cost-saving factors for Medicare in the future, which will drive up Medicare spending but also come with substantial benefit. For example, using information technologies will lead to higher Medicare expenditure, but it also can improve the number of healthier elderly, which will lead to lower medical expenditures overall.[44]

FEM can also be applied to projections for specific medical conditions such as obesity. Based on FEM, Lakdawalla et al. show that obese elderly age 70 or over incur approximately $39,000 in additional medical cost compared with those who are not obese.[45] Some studies also focus on the impact of particular treatments, such as the HPV vaccine.[46]

2.2.5. Conclusion

Dynamic microsimulation models are flexible demographic projection tools which have been used very often recently. As mentioned previously, the transition probability matrix is the heart of microsimulation models. In general, these microsimulation models use disability status, which can be also referred to as health status in some of the previous models, as an important component for projection. Table 2-3 describes how previously discussed models measure and define disability (health) status.

Table 2-3: Summary of Microsimulation Models

Name of model	Approaches to estimate disability (health) status
CBOLT	• Adopting incidence rates of disability for recipients of Social Security Disability Insurance by age and sex
DYNASIM	• Adopting work limitation status from SIPP
LTCFM	• Using probability estimated from NLTCS and NNHS • ADLs and IADLs are the measurements
FEM	• Functional limitations: bending and lifting • ADLs and IADLs are the measurements

Based on Table 2-2, disability status is the most commonly used term to represent health status. In this dissertation, disability status is not the only factor that will be included in the definition of LTCS. Besides ADLs and IADLs, which are the most common measures for functional disability, functional limitations including bending the lower back, walking for two blocks, and reading can also be considered supplementary components for measuring functional disability. Assistance needed for functional disability does not require medical professionals; on the other hand, assistance required for medical services such as dialysis, tube feeding, and urinary catheter will need skilled personnel. Given that, adapting the level of need for medical services and other skilled LTC services is necessary for projecting future LTC expenditures.

2.3. Dataset: Wisconsin Long Term Care Functional Screen

The Wisconsin Long Term Care Functional Screen (WI-LTC-FS) is not a self-reported dataset because the screeners have to meet qualification requirements such as education level, LTC assessment experience, and training certification to conduct the evaluation. Many studies have shown that administrative claims data is suitable for evaluating health care utilization that can offer the most complete information for care recipients,[47,48] and it is a reliable source in health care utilization evaluation.[49] Administrative medical data can reduce misinterpretation caused by self-reported data, especially due to the recipient's mental or cognitive status—both of which are highly related to those who need LTC services.[49–53] Sibley et al. (2010) also supported the assertion that administrative data is good to use for planning, reimbursement, and assessing quality of health care utilization. Therefore, this data can be considered more reliable than self-reported data or traditional administrative data. Based on users' input and statistical proof, this screen has acceptable levels of validity and reliability.

WI-LTC-FS was developed by experienced LTC assessment and eligibility professionals since 1997, and it is different from other well-known screens or assessments such as Minimum Data Set (MDS), which is completed by nursing homes, and OASIS, which compiles the forms that home health agencies must complete. WI-LTC-FS is different because it needs to be applicable for five different target groups: frail elderly, physical disability, developmental disability, dementia, and terminal condition with death expected within one year from the date of eligibility for LTC services.

The screen will be conducted annually to determine continued eligibility for the LTC program; however, the functional screen needs to be updated and re-evaluated if the conditions of persons enrolled in the LTC program change significantly. Meanwhile, the functional screen can be re-conducted if someone requests it. The functional screen is conducted by screeners via face-to-face interviews with consumers, and additional information can be obtained from family members, significant others, or health care providers.

WI-LTC-FS houses approximately 200 measures for each recipient to assess assistance need for ADL, IADL, health-related tasks, diagnoses, and behavioral symptoms and cognitions. In addition, WI-LTC-FS contains information on basic demographics, current and preferred health care setting situation, mental health status, substance use, and other risk factors.

Although the WI-LTC-FS dataset is not a public dataset, a copy of this longitudinal data is maintained by the Center of Health Systems Research and Analysis (CHSRA)[IV] under contract with the Wisconsin Department of Health Services, Division of Long Term Care (DLTC) who allowed. CHSRA provide a de-identified copy of the WI-LTC-FS to support this dissertation. Appendix A is a full copy of WI-LTC-FS data collection form.

[IV] The Center for Health Systems Research and Analysis (CHSRA) was formed in 1973 as a collaborative effort between the departments of Industrial Engineering and Preventive Medicine at the University of Wisconsin-Madison. At CHSRA, researchers seek to improve long-term care and health systems by creating performance measures and developing information and decision support systems.

2.4. Long Term Care Program Capitation Rate Formula

This research applies the Family Care capitation regression formula on individuals' WI-LTC-FS values to define LTC status at monthly LTC cost level. The Wisconsin Department of Health Service contracts with PricewaterhouseCoopers (PwC) for developing calendar-year Family Care monthly capitation payments; PwC has published annual reports for approximately 10 years. The capitation rate is based on Managed Care Organizations' encounter data with adjustments based on Family Care recipients' WI-LTC-FS. It uses base data from two years ago to estimate the monthly capitation rate for the current calendar year. Each eligible target group—developmentally disabled, physically disabled, and frail elderly—has an independent regression model. The regression models vary slightly from year to year. This dissertation adopts the latest frail elderly regression model launched in 2012 by PwC because the population included in this study is elderly.

Family Care capitation rate regression modeling processing occurs in a stepwise manner; it starts with variables that explain the most variation and then adds variables from the base data set that have a marginally decreasing effect on improving the model's R square value and increasing the model's overall predictive capacity. The schematic representation of the regression model is given below.

$$Outcome\ variable = (\beta_0 + \beta_1 \times Variable\ 1 + \beta_2 \times Variable\ 2 + \ldots + \beta_n \times Variable\ n) + \varepsilon$$

Included in the regression model are many variables categorized into 8 classes based on the WI-LTC-FS categories built by PwC in 2012. Variables and estimated coefficients included in the Family Care capitation rate regression model for the frail elderly population are presented in Table 2-4, and the variables are defined as follows based on PwC definitions.[54]

All variables are coded as dummy variables in the regression model, which shows whether or not a Family Care recipient has particular characteristics. Variable IADL_2, for example, represents that a recipient has two distinct IADL limitations; thus, it is clear that the total number of IADL limitations has a more significant impact on current cost than the type of IADL limitation. On the other hand, knowing the type of ADL limitation is vital for capitation rate estimation; moreover, the level of assistance for specific ADLs or IADLs also has a significant impact. Bathing_1, for example, represents that a recipient requires assistance for bathing but the helper does not have to be physically present throughout the task; moreover, dressing, which does not have any numbers associated with it, means that a recipient's need for assistance with dressing will be included regardless of the level of assistance required. Several interaction terms derived from WI-LTC-FS affect LTC services costs; the interaction between autism and symptoms of depression is just one example.

This study estimates individuals' total expected LTC costs using the published PwC capitation regression formula and categorizes them into one of five statuses, which is called LTC status (LTCS). Classifying members into one of these five categories each year, a basic observed annual transition rate matrix can be constructed. The details of the observed annual transition rate matrix will be discussed in Chapter 3.

Table 2-4: Variables and Estimated Coefficient in Frail Elderly Family Care Capitation Rate Regression

	Variables (Estimated Coefficient)
NH level of Care	SNF (318.25) Dual Enrollee (342.57)
Number of IALDs	IADL_2 (239.38) IADL_3 (362.44) IADL_4-5-6 (629.01)
Specific ADLs	Bathing_1 (130.36) Bathing_2 (367.10) Dressing (125.90) Toileting_1 (198.79) Toileting_2 (554.35) Transfer_2 (220.56)
Interaction Term	Transfer_Equip_Mobility (220.33) Autism_Depression (1839.84) Brain Injury Pre-22_anxiety Disorder (1622.81) Seizure Pre-22_Depression (882.33) Seizure Post-22_Anxiety Disorder (268.45)
Behavioral Variables	Resistive (146.22) Offensive (235.45) Mental Health (136.72) Substance Abuse (233.48)
Medication Use	Meds_2A (64.89) Meds_2B (367.08)
Health Related Service	Overnight (208.12) Nursing (206.07) Reposition (285.64) Exercise (180.17) Tracheostomy (1030.95) Ulcer Stage_2 (231.61)
Diagnoses	Alzheimers (94.37) Mental Illness (353.01)
Estimated Intercept: 194.48 Source: PwC 2012	

2.5. Research Aims

This research is based on the payer's perspective, so an individual's health status, LTCS, is based on the expected monthly managed care LTC program capitation rate. There are three reasons why this dissertation uses capitation rate level to define LTCS: (1) the expected capitation rate is readily available and estimated by actuarial techniques that identify explanatory variables that affect total current LTC services cost, including skilled and unskilled LTC services, (2) the modeling process will not be affected by noise exhibited in actual costs, and (3) the result can be generalized to other states as every state has set its own capitation rates for managed care LTC program enrollees.

There are four specific research aims:

(1) To identify factors that can predict the future capitation rate given the current capitation rate among Wisconsin Medicaid managed LTC program enrollees from 2008 to 2010.

(2) To identify a simple parametric form to model the annual transition rates among managed LTC recipients.

(3) To test the resulting model using additional data for 2011

(4) To suggest applications of the model in projecting future program cost and as the basis for assessing quality of care provided by MCOs.

Chapter 3. **Development of Long Term Care Status Transition Matrix**

The aim of this step is to develop a state-based transition model for predicting an individual's future capitation level. The parametric forms are developed via maximum likelihood multinomial logistic regression.

3.1. Data Sampling

The target population for this study are Wisconsin managed Family Care program enrollees aged 60 and over from 2008 to 2010. Family Care, authorized by the state legislature in 1998, is an LTC service system that provides services through nursing homes, community-based living facilities, and home health programs, while recognizing the need for interdependence and support from the family and functional screen.[55] First, we use Family Care monthly enrollment data to identify whether individuals were enrolled in the program during the census month, June. This study sets June 30 as the census date for each year, and has chosen the most recent functional screen at three census dates from 2008 to 2010 for these recipients. The identified WI-LTC-FS can be marked as either valid or not valid. The functional screen will be marked as not valid when it contains missing values or it has not been updated for more than one year. Because the sample covers three years, two transition activities—from 2008 to 2009 and from 2009 to 2010—are examined. The transition activities from 2010 to 2011 are used to validate the model. Individuals with valid functional screens at the starting and ending census years are included for the transition model construction, and individuals who died in the ending years are included as well. Thus, individuals who left the Family Care program and those without valid functional screens in the ending year are excluded. There are 22,290 valid transition activities. One recipient may have information on two transition activities, and those who were enrolled only in 2009 or 2010 are excluded.

Figure 3-1 displays the process of extracting valid transition activities for the model construction. There are 9,544 eligible transition activities from 2008 to 2009, and 12,746 from 2009 to 2010. There are 451individuals excluded in 2009 because they did not have valid functional screens or were not enrolled in the program. Additionally, 1,243 individuals passed away between the 2008 and 2009 census dates. 5,248 new enrollees joined the program in 2009 and 803 enrollees either left the program or did not have valid functional screens between the 2009 and 2010 census dates.

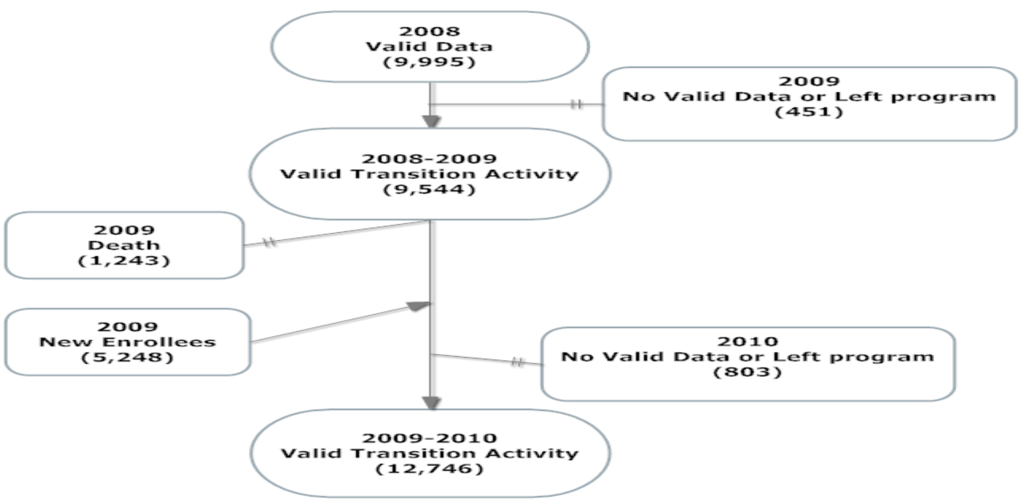

Figure 3-1: Sample Selection Flow

The LTC capitation rate formula shown in chapter 2.4 can be applied to each individual’s valid WI-LTC-FS; the expected capitation rate is categorized into one of five statuses based on the expected cost level at the three census dates. Status A (LTCS=A) has the lowest capitated cost, and status E (LTCS=E) has the highest capitated cost. This study defines LTCS as capitated cost level and partitions five status ranges spread evenly across the entire range of capitation values. The five status ranges are: <$1,050; $1,050-$1,650; $1,650-$2,250; $2,250-$3,050; and >$3,050.

The observed transition rate matrix (π) is constructed based on the individual's capitation rate level (LTCS) as observed at three specific census dates. Table 3-1 shows the numbers of individuals with combinations of starting and ending LTCS, and the corresponding transition rates. The diagonal represents the probability of staying at the same status over a year, and it indicates that most individuals remain at the same status over a year. The upper diagonal area represents the probability of impairment, and the lower diagonal area represents the probability of improvement. Overall, the probability of improvement is lower than impairment. Death is set as an additional ending LTCS, and this column shows that the high capitation rate population has a higher risk of death over a year.

Table 3-1: Observed Transition Rates

Starting LTCS	**Ending LTCS**						
	A	**B**	**C**	**D**	**E**	**Death**	**Total**
A	2202 (66.3%)	660 (19.9%)	156 (4.7%)	76 (2.3%)	59 (1.8%)	166 (5.0%)	3319 (100.0%)
B	469 (9.9%)	2730 (57.8%)	739 (15.6%)	310 (6.6%)	156 (3.3%)	323 (6.8%)	4727 (100.0%)
C	60 (1.4%)	493 (11.3%)	2077 (47.6%)	999 (22.9%)	309 (7.1%)	429 (9.8%)	4367 (100.0%)
D	21 (0.4%)	84 (1.7%)	548 (10.8%)	2688 (52.9%)	1050 (20.6%)	694 (13.6%)	5085 (100.0%)
E	5 (0.1%)	29 (0.6%)	65 (1.4%)	466 (9.7%)	3002 (62.6%)	1225 (25.6%)	4792 (100.0%)
Grand Total	**2757 (12.4%)**	**3996 (17.9%)**	**3585 (16.1%)**	**4539 (20.4%)**	**4576 (20.5%)**	**2837 (12.7%)**	**22290**

3.2. Candidate Factor Selection

Ideally, it would be nice to understand how factors such as gender and age affect the transition rates. Therefore, Table 3-2 and Table 3-3 show the same information broken down by gender. Clearly, data for some cells is sparse. Because of this sparseness, valid estimates of stratified transition probabilities cannot necessarily be based solely on the observed data within each strata. The sparseness problem will only be intensified by stratifying the data into more levels based on factors such as age. For example, after the transition data is stratified by gender and then again by age levels (60-72, 73-85, and >85), some cells contain no observations.

This research looks for a parsimonious parametric model to estimate the effect (β) of potential factors such as gender and age given the current capitation rate level (LTCS), rather than deconstructing data by gender and age as shown in Table 3-2 and Table 3-3. This method of model construction can minimize sparse data problems and provide a standard way to model transition rates for individuals. In short, this approach puts the data to its best use.

Table 3-2: Observed Transition Rate--Female

Starting LTCS	**Ending LTCS**						
	A	**B**	**C**	**D**	**E**	**Death**	**Total**
A	1674 (66.8%)	510 (20.4%)	118 (4.7%)	51 (2.0%)	47 (1.9%)	106 (4.2%)	2506 (100%)
B	357 (10.1%)	2037 (57.7%)	545 (15.4%)	236 (6.7%)	122 (3.5%)	236 (6.7%)	3533 (100%)
C	37 (1.2%)	346 (11.3%)	1443 (47.2%)	706 (23.1%)	232 (7.6%)	290 (9.5%)	3054 (100%)
D	18 (0.5%)	63 (1.8%)	378 (10.7%)	1855 (52.4%)	758 (21.4%)	469 (13.2%)	3541 (100%)
E	4 (0.1%)	24 (0.7%)	48 (1.4%)	322 (9.3%)	2197 (63.3%)	875 (25.2%)	3470 (100%)
Grand Total	**2093 (13%)**	**2980 (18.5%)**	**2532 (15.7%)**	**3170 (19.7%)**	**3356 (20.8%)**	**1976 (12.3%)**	**16104**

Table 3-3: Observed Transition Rate--Male

Starting LTCS	Ending LTCS						
	A	B	C	D	E	Death	Total
A	528 (64.9%)	150 (18.5%)	38 (4.7%)	25 (3.1%)	12 (1.5%)	60 (7.4%)	813 (100%)
B	112 (9.4%)	693 (58.0%)	194 (16.2%)	74 (6.2%)	34 (2.8%)	87 (7.3%)	1194 (100%)
C	23 (1.8%)	147 (11.2%)	634 (48.3%)	293 (22.3%)	77 (5.9%)	139 (10.6%)	1313 (100%)
D	3 (0.2%)	21 (1.4%)	170 (11.0%)	833 (54.0%)	292 (18.9%)	225 (14.6%)	1544 (100%)
E	1 (0.1%)	5 (0.4%)	17 (1.3%)	144 (10.9%)	805 (60.9%)	350 (26.5%)	1322 (100%)
Grand Total	**667 (10.8%)**	**1016 (16.4%)**	**1053 (17.0%)**	**1369 (22.1%)**	**1220 (19.7%)**	**861 (13.9%)**	**6186**

Many studies have been conducted to identify risk factors causing decline or improvement in disability or functional status, since disability and functional status are used widely to predict LTC-related issues. This step of this research aims to identify possible factors that can be used in a parsimonious transition model to predict future LTCS. The algorithm used to search and decide among variables follows a literature review and a discussion of data availability.

Migrations between functional disability statuses are caused by many different factors; knowing the current status does not necessarily reliably predict the next status without considering such factors. Gender and age are the most common and obvious risk factors discussed in many previous studies.[56–59] Moreover, from the LTC program administrators' point of view, gender and age are the mostly easily assessed and accessed points of information from individuals. Moreover, the values of gender and age over a year are stable and progress over time in a known manner.

In order to manage Medicaid LTC programs, policymakers and administrators are also interested in LTC setting capacity planning. Information on living situation is also available on WI-LTC-FS. Besides, whether the individuals being studied were institutionalized or not is also suggested by previous studies as a potential risk factor.[9,33,59,60] Several studies use living arrangement as an indicator for disability status, i.e., living in community assisted living with a disability or living in a nursing home.[6,60,61] In addition, research has identified notable improvements in functional disability status among community assisted living residents in the long run,[62,63] while residents in nursing homes were more likely to remain in the same functional status.[64,65] Therefore, living arrangement is another potential risk factor.

Based on a literature review and LTC program administrators' standpoints—as well as the availability of this information in WI-LTC-FS—gender, age, and living arrangement are the potential risk factors that will be addressed in this dissertation. Yet, as discussed in chapter 2.3, WI-LTC-FS includes approximately 200 potential risk factors, which can be divided into ten categories: demographics, living arrangements, ADLs, IADLs, overnight care requirements, employment situation, diagnoses, health related services requirements, communication and cognition, and behavioral/mental status. Therefore, the identified risk factors are not the only choices. However, using some risk factors such as ADL, IADL, and diagnoses increases the difficulty of applying the research findings to data from other states because these types of data are not typically easy to access and assess.

Additionally, while examining the possible risk factors from available data, some factors are not included due to the characteristics of the target population. For example, although employment situation is also a possible factor, 96% of the target population in this dissertation was unemployed or retired. Additionally, this dissertation focuses on the Medicaid-eligible elderly population, and employment may affect eligibility for the Medicaid program. Therefore, this research chooses not to include employment situation in the model.

To sum up, among all of the possible and available variables, this dissertation will focuses on (1) gender, (2) age, and (3) living arrangement. Other possible factors will be a valuable research extension in the future. Each variable is set as a categorical variable, as described in Table 3-4.

Based on the individual's age in the starting year, which is either 2008 or 2009, this study categorizes individuals into three levels: 60-72, 73-85, and >85. The sample sizes in each category are approximately the same. Individuals are also assigned one of four categories for their current living situation: living at home alone; living at home with a helper; community assisted living; and nursing home. WI-LTC-FS defines current living situation in 23 different types. This study groups them into 4 main categories. The details of the current living situation information can be found in the WI-LTC-FS appendix. Table 3-4 shows the characteristics of the sample.

Table 3-4:Description of Sample Characteristics In Transition Matrix	
Total Sample Size	22,290
Enrolled in 2008	9,429 (42.3%)
Enrolled in 2009*	12,861 (57.7%)
Gender	
Female	16,104 (72.2%)
Male	6,186 (27.8%)
Start LTCS	
A (<$1,050)	3,319 (14.9%)
B ($1,050-$1,650)	4,727 (21.2%)
C ($1,650-$2,250)	4,367 (19.6%)
D ($2,250-$3,050)	5,085(22.8%)
E (>$3,050)	4,792(21.5%)
Age	
60-72	8,468 (38.0%)
73-85	8,696 (39.0%)
>85	5,126 (23.0%)
Living Situation	
Home-Alone (HA)	6,747 (30.3%)
Home-With Someone (H)	6,790 (30.5%)
Community Assisted Living (C)	6,264 (28.1%)
Skilled Nursing Facilities (I)	2,489 (11.2%)

* Including recipients were also enrolled in 2008

3.3. Maximum Likelihood Multinomial Logistic Regression

A suitable type of multiple-state model to represent the complex process of multiple status transitions with categorical independent variables is maximum likelihood multinomial logistic (MLML) regression. The MLML is a generalized type of logic regression that allows more than two categorical values for the dependent variable. When using multinomial logistic regression, one category of the dependent variable is chosen as the reference category. The MLML can be viewed as a set of binary logistic regressions, and all other dependent categories are regressed against the reference category separately.[66] Odds ratios (OR) are estimated and shown as e^{β} for all independent variables for each dependent variable category and 1 for the reference category. In addition, one of the categories within a each categorical independent variable is chosen as the reference group as well.

This model uses the Catmod Procedure developed by SAS to conduct the MLML. SAS Catmod is a powerful statistical package that implements maximum likelihood (ML) estimation of parameters for log-linear models and the analysis of generalized logistics.[67,68] It has been widely used for MLML analysis. The following paragraphs will discuss how this research manipulates the data and software to overcome the limitations caused by SAS default settings.

The outcome of interest (dependent variable) in this research is LTCS=A, B, C, D, E, or death one year hence, given the current LTCS. Transition to LTCS=E was automatically chosen as the reference category by SAS Catmod due to alphabetical order of outcomes. For the demographic variables, male and the highest age level (>85) were chosen as reference categories by SAS Catmod default setting. For the living arrangement variables, the reference category was the group living in the nursing home. The results are reported as log-odds ratios (β).

Interpretation of the odds ratios in multinomial logistic regression is difficult to provide. Statistically speaking, we have the $\beta_{ij}^{Female} = Ln\left(\frac{P_{ij}^{Female}/P_{ij}^{Male}}{P_{iE}^{Female}/P_{iE}^{Male}}\right)$ where P_{ij}^{S} is the probability that a female participants moving from status i to status j. In addition, β_{ij}^{Female} represents the coefficient for female with starting LTCS=i and ending LTCS=j. This estimate explains only the comparison between one outcome status and the reference outcome status, and gives only a relative value, not an absolute value. For example, β^{F}_{BA}=2.3 does not mean that females are more likely than males to move to LTCS=A; instead, it describes that compared to the male, the female is more likely to move to LTCS=A given the assumption that they move to either LTCS=A or LTCS=E (reference group).For another example, $\beta_{ij}^{60\text{-}72}$ represents the coefficient for aged 60-72 population with starting LTCS=i and ending LTCS=j. Therefore, exponential

β_{CD}^{60-72} =0.1 means that compared to the reference age group (>85), people aged 60-72 are less likely to moving from LTCS=C to LTCS=D given the assumption that they can only move to either LTCS=D or LTCS=E (reference group). For the exponential function of beta, if beta is negative, the exponential of beta will be smaller than 1 and the movement form i to j is less likely than the reference population.

The transition probability from a starting LTCS to an ending LTCS is shown as:

$$P_{ij} = \frac{e^{\beta_{ij} X_i}}{\sum_{k=A}^{Death} e^{\beta_{ik} X_i}}$$

i: starting LTCS i is A, B, ……and E

j: ending LTCS j is A, B, ...E, and Death

β_{ij}: a vector of regression coefficients associated with starting status LTCS=i and the ending status LTCS=j

X_i: a vector of explanatory variables associated with the starting LTC= i

We present the youngest (aged 60-72) group of male individuals with starting LTCS=A as an example shown in Table 3-5. This example demonstrates the effect of living in community assisted living on given ending LTCS. The intercepts represent the effect of the reference population (male, aged 60-72, and living at home either with a helper or not) on given ending LTCS compared to LTCS=A (reference group). The coefficient represents the additional adjustment on top of effect for reference group (living at home) of community assisted living on given ending LTCS compared to no status change.

Although the coefficient of community assisted living on LTCS=E is 22.48, the probability of moving from LTCS=A to E for the youngest male community assisted living population does not increase dramatically. The $P_{ij} = \frac{OR_j \times X_i}{\sum_{j=A}^{Death} OR_j \times X_i}$, the probability of transferring from LTCS=A to LTCS=E for the reference population (the population living at home) is calculated by $\frac{0.02}{1+0.27+0.06+0.03+0.02+0.08} = 1.37\%$. An adjustment is required for those who live in community assisted living. The coefficient of community assisted living compared to living at home (reference population) represent the impact of living in community assisted living on ending LTCS compared to no status change (LTCS=A). For example, the probability of transferring from LTCS=A to LTCS=E for the youngest male community assisted living population is calculated by $\frac{0.02\times22.48}{(1\times1)+(0.27\times7.03)+(0.06\times10.62)+(0.03\times10.62)+(0.02\times22.48)+(0.08\times13.07)} = 8.41\%$.

The reference group is composed of individuals whose status does not change, and thus the coefficients for ending LTCS=A are 1 for both the intercept and living situation adjustments. Yet, the probability of staying at the same status decreases from 68.49% to 18.69%. The effect of living situation changes the distribution of probability for ending LTCS, but the effect may not be as dramatic as the number.

Table 3-5: Multinomial logistic regression coefficients for aged 60-72 male individuals starting in LTCS=A

	A	B	C	D	E	Death
Intercept	1	0.27	0.06	0.03	0.02	0.08
Living in Community Assisted Living or Nursing Home	1	7.03	10.62	10.62	22.48	13.07
Probabilities for Reference Population	68.49%	18.49%	4.11%	2.05%	1.37%	5.48%
Probabilities after living situation adjustments	18.69%	35.48%	11.91%	5.96%	8.41%	19.55%

The default of the SAS Catmod procedure provides a basic understanding of multinomial logistic regression; however, comparing to a fixed reference group for all starting statuses makes it difficult to understand and interpret the relationships of improvement, impairment, or no change from the current status. Therefore, this dissertation proposes new modeling strategies. The details of these strategies will be discussed in the following section.

3.4. Modeling Strategies

As mentioned previously, MLML has fix reference group for dependent variable which leads the difficulty of finding the association between coefficients. In addition, the traditional coefficients cannot provide a direct explanation regarding the relationship between current and future LTCS. The observed transition rates shown in Table 3-1, there is a strong association between those with the same relationship between current and ending status.

3.4.1. Redefine Dependent Variables and Reference Group

Instead of the ending LTCS alone, as discussed previously, the change between starting LTCS and ending LTCS is used as a new outcome of interest. There are 10 possible new outcomes representing the level of improvement or impairment, no change, and death. For instance, -1 represents one level of impairment from the starting status (i.e., from LTCS=A to LTCS=B), and +1 represents one level of improvement from the starting status (i.e., from LTCS=C to LTCS=B). However, certain outcomes are not available to specific starting statuses. For example, starting status A has no improvement outcomes available, and impairment outcomes are not available with starting status E. Moreover, only two level of improvement and impairment are available for starting LTCS=C.

Table 3-6 shows all possible outcomes corresponding to each starting status. Each starting status has six possible outcomes. The reference group of outcomes is “no change.” Thus, the corresponding estimate can provide more meaningful and interpretable information. Moreover, this approach reveals the ordinal relationship between outcomes, and provides a guideline for further estimation. Based on the inconsistent possible outcome options for each starting status, developing a separate transition model is necessary.

Table 3-6: Relationship between starting and ending LTCS

Starting Status	Ending Relationship									
	Death	-4	-3	-2	-1	No Change	+1	+2	+3	+4
LTCS=A	√	√	√	√	√	√				
LTCS=B	√		√	√	√	√	√			
LTCS=C	√			√	√	√	√	√		
LTCS=D	√				√	√	√	√	√	
LTCS=E	√					√	√	√	√	√

3.4.2. Empirically Test for Candidate Independent Variable by Starting LTCS

As noted previously, this research focuses on starting status, gender, age, and living arrangement. Each starting LTCS has a different set of transitions as noted in Table 3-6. Therefore, we conduct the variable selection process separately for each starting LTCS. The criterion for including variables is based on a *chi-square* test at 5% significance level.

First, this study conducts a single independent variable multinomial logistic regression on all potential variables and eliminates those variables that show no significant impact. Second, we then conduct a multiple independent variables regression to test whether including two or three of the variables that were significant individually can improve the ability to explain the variation between transition rates. Interactions between the included variables are tested as well. The most complex model that shows a statistically significant difference from the simpler models is selected.

Table 3-7 shows the results of the variable selection process. The boxed entry for each starting LTCS is the final model chosen. In Table 3-7, the base model includes only the starting LTCS. The chi-squared value for each possible single variable regression model is relative to the base model. The chi-squared value for each possible multiple variable regression model is relative to the model with the rightmost factor excluded (i.e., a model with one less independent variable). In other words, when the *chi-square* test for S+A+L is stated, this means that adding L yields a statistically different prediction than a model with only S+A. Similarly, the chi-squared value for each possible interaction term model is relative to the same model without the interaction terms.

Based on the criterion, gender is statistically significant only when the starting status is A, the lowest cost group. The gender effect vanishes as recipients move into higher cost groups. Both age and current living situation are consistently significant for all starting LTCS. Moreover, the interaction between age and current living situation is significant for starting statuses A

Table 3-7:Included Variables by Each Starting LTCS

Starting LTCS	Base	Single Additive			Multiple Additive Terms				Interaction Terms			
A												
		S	A	L	S+A	A+L	S+L	S+A+L		S+A+L+(S×L)	S+A+L+(A×L)	S+A+L+(S×A)
Number of Estimations	5	10	15	20	20	30	25	35		50	65	45
Chi-Square		15.9**	58.0**	52.4**	21.7**	44.3**	15.7**	43.6**		11.1	44.6*	12.3
B												
		S	A	L	S+A	A+L	S+L	S+A+L	A+L+(A×L)			
Number of Estimations	5	10	15	20	20	30	25	35	60			
Chi-Square		2.7	143.4**	130.5**	-	103.2**	-	-	29.2			
C												
		S	A	L	S+A	A+L	S+L	S+A+L	A+L+(A×L)			
Number of Estimations	5	10	15	20	20	30	25	35	60			
Chi-Square		7.5	180.7**	282.7**	-	255.3**	-	-	35.2			
D												
		S	A	L	S+A	A+L	S+L	S+A+L	A+L+(A×L)			
Number of Estimations	5	10	15	20	20	30	25	35	60			
Chi-Square		9.4	186.8**	186.6**	-	175.8**	-	-	43.8			
E												
		S	A	L	S+A	A+L	S+L	S+A+L	A+L+(A×L)			
Number of Estimations	5	10	15	20	20	30	25	32	60			
Chi-Square		5.9	201.8**	161.6**	-	134.2**	-	-	63.4**			

S:Sex
A:Age
L:Current Living Situation
*:*P-Value*≤0.05 **:*P-Value* ≤0.01

3.4.3. Methodology for Independent Variable Coding

The SAS Catmod default calculation for multinomial logistic regression is not appropriate for research questions addressed by this dissertation. There are two main problems: (1) SAS Catmod estimates the effects of each categorical level of a given independent variable separately; and (2) SAS Catmod has a limited ability to estimate effects in sparse populations. Each problem will be discussed in the following paragraphs.

One of the research goals is to propose a simple parametric form to model the transition rates for all individuals. Therefore, minimizing the number of categorical levels for any given independent variable is required. However, testing whether a given categorical level of an independent variable can be eliminated is difficult, because the effects of each level of a given independent variable are estimated individually based on SAS Catmod default settings. The problem is that, with the usual coding of independent variables, it is difficult to conveniently test whether the effect of one level is the same as a neighboring level. The cumulative code scheme makes such testing more convenient. In order to provide a convenient and scientific way to group levels of the independent variables, we code the independent variables such as age and living arrangement cumulatively. Taking age as an example, this study partitions age into three levels: 60-72; 73-85; and >85. The model intercept terms assume that the individual is in the youngest age group. Adjustments are added if the individual is 73 or older and, again, if the individual 85 or older. In other words, an individual aged 87 will trigger both adjustments. That is, the coefficient associated with the last age group is the additional effect of being 85 or older, plus the effect of being 73 or older. This seems to be more reasonable than testing whether the last age group is significantly different from the first age group (or reference group).

Similarly, this study assumes that there may be a hierarchical relationship among living situations. This study sets the hierarchical relationship based on the individual's ability to be independent. Individuals living at home alone are assumed to be the most independent, and individuals who live in nursing homes are assumed to be the least independent. The lowest (intercept) level is living alone at home (HA) followed by living at home with a helper (H), then residing in a community assisted living facility (C) and, finally, living in a nursing home or institution (I). The characteristics of the nursing home population are believed to be more similar to the community assisted living population than to the living at home population. Thus, this study assumes that the adjustment for living at home with a helper will also be added to those who live in an assisted living setting or in a nursing home; likewise, the adjustment for those in assisted living also applies to those who live in a nursing home. That is, the coefficient associated with the nursing home is the additional effect of living in a nursing home over and above the effect of living in community assisted living and at home with helpers.

This approach provides a rigorous way to minimize the categorical levels given an independent variable, because testing the significance of the additional effect of each categorical level is equivalent to testing the significance of the effects of the last two groups. Thus, this approach solves the first problem of SAS Catmod default setting. But this approach still provides a flexible parametric form to model data without any constraints. For example, the coefficient of living in a nursing home is not significant, and this shows that the estimations for both living in a nursing home and community assisted living (prior group) are equal.

As shown in Table 3-7, different starting statuses include different variables to explain the variations for future LTCS, and thus this research conducts MLML regression using an original parametric format for each starting status separately. However, certain combinations of data are sparse, because these situations rarely exist and there are not enough samples in the dataset. For example, if a recipient starts at LTCS=E, is >85, and lives in an institutional care setting, it is very rare that that recipient will improve to LTCS=A next year, but it is not impossible. The incomplete observation due to sample attrition leads SAS Catmod procedure to estimate these sparse samples as positive infinite or negative infinite estimations to fit the model; these estimations are indicated as # in the estimation output. The estimations with the # sign are not valid. This study merges these missing data with prior categories to solve this problem. For instance, the population with starting LTCS=E, aged >85, and living in institutional care is merged with those who have the same starting status and age category but live in assisted living. The cumulatively coded approach suggests a convenient way to group the sparse samples.

SAS Catmod allows users to create their own design matrix to address research questions as needed. Instead of using the default SAS Catmod design matrix, this dissertation develops an efficient algorithm in Microsoft Excel to generate appropriate design matrixes. This provides the flexibility of grouping the levels not only given an independent variable, but also given dependent variables. For example, the tool developed by this dissertation can set the algorithm so that gender has the same impact on ending relationships of -3 (D) or -4 (E) when starting at LTCS=A. The cumulatively coded approach allows this study to test whether additional adjustment is necessary for all the levels of each respondent variable at a 10% significance level by using the “contrasts” command in SAS Catmod. The “contrasts” command is performed with respect to all the possible outcomes. If the estimation of additional adjustment does not show significance, the higher level of category can be combined with the previous level. For example, for starting statuses A and B, the impact of living with a helper at home (H) is merged with the prior category of living at home alone. This approach overcomes the two problems of limited datasets and limited capability for minimizing categorical level given an independent variable and given dependent variables of SAS Catmod.

3.4.4. Sequence of Merging Group

Coding independent variables cumulatively is a flexible approach to grouping samples in a meaningful and convenient way. The aggregation process consists of grouping sparse samples with neighboring samples, followed by testing the significance of the additional adjustment for each categorical level of each independent variable for all possible outcomes, and followed by smoothing estimates given all outcomes.

This dissertation also conducts a *chi-square* to test whether the final model proposed after aggregation process is significantly different from the original model. If useful information is missed during the aggregation process, the parametric format will need further adjustments. Moreover, which step of the aggregation process causes the difference is also tested. The additional model simplifications are shown in Table 3-8. The first column displays the number of parameters and maximum log likelihood for the original model, which were chosen previously and are shown in Table 3-7 for all starting LTCS. If the original model contains sparse samples, the sparse samples will be grouped with neighboring samples by dropping parameters. The second column displays the results after grouping sparse samples. The third column shows the results after aggregating the categorical levels of each independent variable, and the fourth column shows the final model that this research chooses after aggregating the categorical levels of dependent variables if necessary.

Starting LTCS=A can be examined as an example. LTCS=A is the lowest capitation rate group, so the sample size for those who live in nursing homes (I) is sparse. Thus, the first step is to group the nursing home population with the community assisted living population (that is, the neighboring population). Eliminating the additional adjustment of living in a nursing home, which indicates that there is no difference in ending LTCS between community assisted living and living in a nursing home, is a reasonable assumption regarding transition rates. However, the sparse sample situation still exists after grouping these two populations for the interaction terms. Therefore the effects of the interaction term (age × living situations) on ending LTCS=D or E are set to be equal. Once the sparse population problem is solved, this dissertation tests each additional adjustment from each categorical level of a given independent variable on all possible outcomes. The additional adjustment is eliminated as it does not have a significant impact at the 10% significant level. The test shows that the parameters of living at home alone and living at home with a helper are the same, and thus 13 additional parameters can be dropped. In the end, this research identifies that the gender effect for ending LTCS=D and E are the same, so one more parameter is dropped. Although this approach reduces the number of parameters from 65 to 32 as the final model for starting LTCS=A, it still captures the most key characteristics of the data. This dissertation repeats the standard sequence described above for each starting status separately.

For starting LTCS=B, or C, or D, the sparse sample issue does not exist, and thus the process of grouping sparse samples with neighboring samples is not necessary. Therefore, this research directly tests the additional effects of each categorical level of a given independent variable. The results show that the effect of living at home with a helper is the same as living at home alone, and the effect of living in a nursing home is the same as living in community assisted living for starting LTCS=B. Thus, 10 parameters can be eliminated. On the other hand, all categorical levels of a given independent variable for starting LTCS=C or D are significant. Moreover, the results show that all parameters for the dependent variables are significant, so the aggregation technique is not applied for the dependent variables. The test results indicate that the final models with the fewest parameters were not statistically significantly different from the original model, and thus the simpler model is preferable to the original model.

Table 3-8:Aggregation Process

	Original Model	Group Sparse Sample	Test Additional Adjustment	Final Model
Starting LTCS=A	S+A+L+(AL)			
-2Loglikelihood	6769.2	6795.4	6811.5	6813.6
Estimations Number	65	46	33	32
Chi-square		26.2	42.3	44.4
P-value		0.12	0.25	0.15
Starting LTCS=B	A+L			
-2Loglikelihood	12147.8	No sparse data	12162.3	All significant
Estimations Number	30		20	
Chi-square			14.5	
P-value			0.15	
Starting LTCS=C	A+L			
-2Loglikelihood	11891.2	No sparse data	All significant	All significant
Estimations Number	30			
Chi-square				
P-value				
Starting LTCS=D	A+L			
-2Loglikelihood	12503.2	No sparse data	All significant	All significant
Estimations Number	30			
Chi-square				
P-value				
Starting LTCS=E	A+L+(AL)			
-2Loglikelihood	8846.3	8868.2	All significant	8871.0
Estimations Number	60	43		37
Chi-square		21.9		24.8
P-value		0.46		0.83

S: Gender A: Age Level L: Living Arrangement

After some trial and error, the final list of levels for each independent variable and corresponding interaction terms is displayed in Table 3-9. This aggregation process proposes the simplest parametric form with the lowest number of estimations to model the annual transition rates.

Table 3-9:Final List for level of independent variable

	LTCS=A	**LTCS=B**	**LTCS=C**	**LTCS=D**	**LTCS=E**
Female	√				
Age>72	√	√	√	√	√
Age>85	√	√	√	√	√
Live>=H			√	√	√
Live>=C	√	√	√	√	√
Live>=I			√	√	√
Age>72 × Live>=H					
Age>72 ×Live>=C	√				√
Age>72 ×Live>=I					√
Age>85 ×Live>=H					
Age>85 ×Live>=C	√				
Age>85 ×Live>=I					√

3.5. Living Arrangement Transition Model

Determining which explanatory variables to include is complex. Gender, age, and current living situation all play important roles in LTCS modeling. Age and living situation are time-varying explanatory variables, but the change of magnitude for age is fixed. Therefore, using gender and age as explanatory variables to model future LTC status does not require additional prediction through modeling. However, the change of magnitude for living situation varies case by case, and thus a transition model to predict future living situation is necessary.

Given a starting living situation, candidate variables that may help to predict future living situation are starting LTCS, gender, age, and predicted future LTCS. Instead of using current and future LTCS separately, this study uses the change between these two statuses as a potential independent variable labeled “change in LTCS,” as represented by the green lines in

Figure 3-2. Change in LTCS is divided into three categories: improvement, impairment, and staying the same. The new independent variable reduces the number of estimations, but the clinical relationships are still taken into account because living arrangements are highly correlated with LTCS transition rates.

Figure 3-2 represents how this study predicts both future LTCS and future living arrangement. The red lines indicate the potential relationships between independent variables and future living arrangement, while the gray lines indicate the relationships between independent variables and future LTCS. Given LTCS, gender, age, and living arrangement at time t, LTCS and living arrangement at time t+1 can be predicted. The double-line arrows indicate that the predicted LTCS and living situation with gender and age at time t+1 can be used to estimate LTCS and living situation at time t+2. The analytical projection follows this loop.

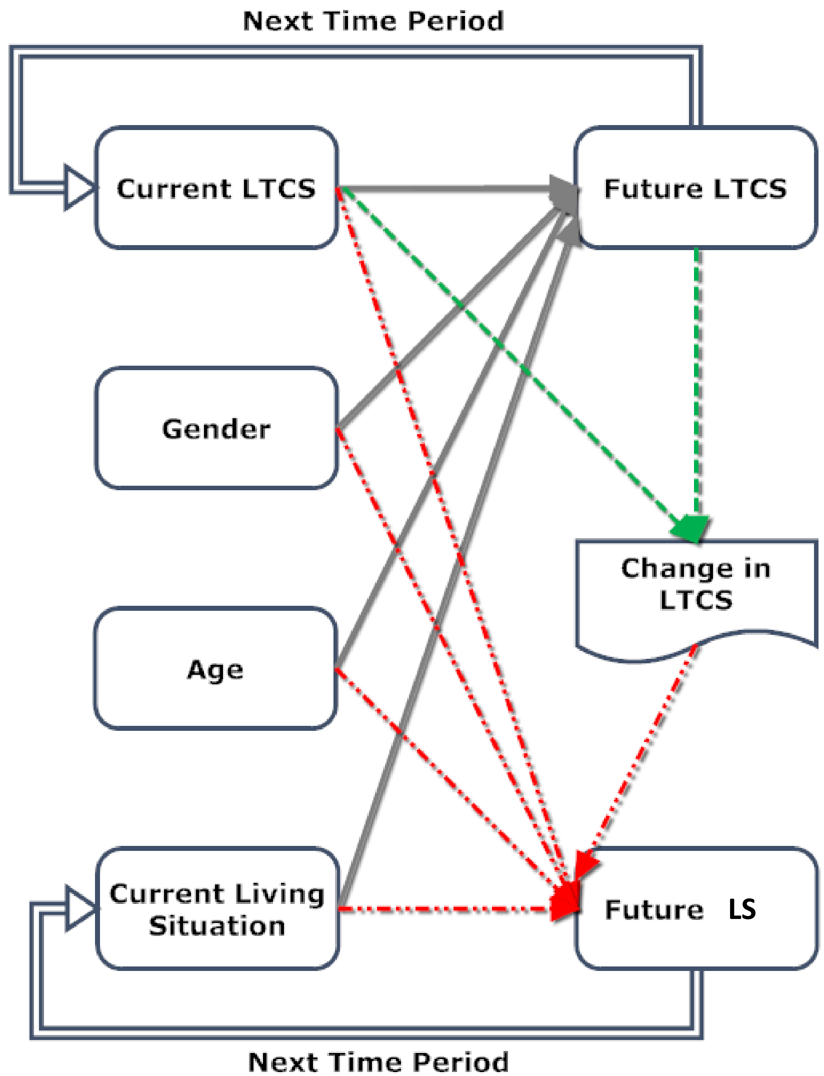

Figure 3-2: Overall Transition Model

Given current living situation, there are four potential independent variables: current LTCS, gender, age, and the change in LTCS. All four potential variables are tested. The process of variable selection follows the same sequence used in chapter 3.4.2. However, the sample size is smaller than the one used for preliminary LTCS modeling, because deceased individuals are removed. The total sample size is therefore only 19,424. This study conducts MLML regression separately for each starting living arrangement.

Table 3-10 displays the details of the variable selection process. The boxed entry is the final model chosen by this dissertation for each starting living arrangement. The base model only includes the starting/current living arrangement. The *chi-squared* value for each possible multiple factor additive model is relative to the model with the "rightmost" factor excluded.
For example, when the *chi-square* test for current LTCS + change in LTCS is shown in column 3, this means that adding change in LTCS yields a statistically different prediction than a model that uses only current LTCS given current living situation (shown in column 2). Gender has a significant impact on those who live at home with a helper (H), but no ability to explain the future living situation variation among those who live at home alone, in a community assisted living facility, or in a nursing home. The interaction impacts between selected variables are also tested, but none of them are significant.

Table 3-10: Included Variables For Each Starting Living Arrangement

Starting Living Arrangement	Multiple Additive Terms				
	Base	**Current LTCS**	**Current LTCS +change in LTCS**	**Current LTCS +Change in LTCS +Age**	**Current LTCS + Change in LTCS + Age + Gender**
Home Alone (HA)					
Number of Estimations	3	15	21.0	27.0	30.0
chi-square		134.0**	1023.0**	67.8**	6.2
Home with Helper (H)					
Number of Estimations	3	15	21	27	30
chi-square		171.1**	445.6**	20.1**	13.6**
Community Assisted Living (C)					
Number of Estimations	3	15	21	27	30
chi-square		56.1**	473.0**	112.9**	3.8
Nursing Home (I)					
Number of Estimations	3	15	21	27	30
chi-square		346.8**	353.6**	18.3**	5.9

*: *p-value*≤0.05 **: *p-value*≤0.01

The cumulative coding approach, which facilitates the process of grouping sparse samples with neighbor samples as discussed in chapter 3.4.3, is also applied here. As LTCS is defined by capitation rate level, a hierarchal relationship exists between the five levels of LTCS (A through E). Therefore, in the living arrangement prediction model, starting LTCS is coded cumulatively when modeling future living arrangement. The following paragraphs explain the details of this approach.

Modeling living situation transition rates also faces the problem that several combinations of independent variables (e.g., female, aged >85, starting LTCS=A, ending LTCS=B, and living in nursing home) have no sample to model. However, SAS Catmod is not capable of handling a zero sample size. Thus, the missing combinations in the dataset are removed from the model. As these samples are excluded in the modeling process, the coefficients estimated by Catmod are valid and reasonable for those combinations that have enough samples. Yet, transition rates for the excluded cases cannot be estimated. Therefore, this dissertation assumes that the transition rates for these combinations are similar to those for their neighbors.

The methodology of identifying neighbors used in this dissertation is discussed below. Five independent variables are used to predict future living situation. Theoretically speaking, this means that five different neighbor groups are available for a group with a zero sample size. For example, we can group a male population with a female population if they have the same age group, current living situation, starting LTCS, and ending LTCS. There is no absolute correct approach to grouping. Therefore, this dissertation follows a methodology based on a literature review and discussion with experts. As mentioned previously, gender is a significant variable only for the population living at home with a helper, and thus identifying a neighbor group with all the same conditions except gender is not appropriate in this dissertation. In addition, previous studies show that populations with different genders and ages have different distributions of living situations.[69,70] Meanwhile, we assume that different combinations of starting and ending LTCS do not share the same living arrangement transition rates. Therefore, this dissertation identifies neighbor groups as populations with all the same independent variables except for current living situation. For example, the dataset does not have a sample that is female, aged >85, starting LTCS=A, ending LTCS=B, and living in a nursing home. Therefore, this study borrows the living situation transition rates from the sample that is female, aged >>85, starting LTCS=A, ending LTCS=B, and living in community assisted living.

This dissertation synthesizes the LTCS transition matrix and living arrangement transition matrix, providing a new status that reflects both capitation rate and living arrangement. Initially, this research constructed 24 (gender=2, age level=3, and living arrangements=4) transition matrixes, each with 5×6 cells (five starting and ending capitation levels, and death status as another ending status). However, after combining the initial matrix with the living arrangement prediction model, six (gender=2 and age level=3) comprehensive transition matrixes are developed, each with 20×21 cells, because the new status definition combines current capitation and living situation (5×4=20).

Therefore, there are six 20×21 transition matrixes used in our projections. The corresponding coefficients and probabilities will be discussed in Chapter 5.

3.6. Markov Assumption Test

This dissertation develops its transition model as a first-order Markov model, in which the probability of moving to the next status depends only on the current status, not on any past statuses. In addition, this dissertation identifies factors that can improve the ability to predict the next status given the current status, as discussed previously. By contrast, many previous studies focused first on testing first-order versus second-order Markov assumptions rather than identifying additional factors first.[71,72] A second-order Markov model is defined as the probability of moving to the next status depending on both the current and immediate prior statuses. The null hypothesis is that the successive events are a first-order Markov chain is tested against the alternative hypothesis that transitions follow a second-order Markov chain.

Therefore, this dissertation also tests the second-order Markov assumption given additional independent variables. An MLML is conducted to evaluate the additional impact of immediate prior LTCS given current LTCS, gender, age level, and living arrangement, as well as the unconditional impact of prior LTCS on future LTCS without any other independent variables such as gender and age. Both show that the prior LTCS is statistically significant at a 5% level. Table 3-11 shows the *chi-square* results for both conditional and unconditional impacts of prior LTCS. Therefore, the effect of prior LTCS has been confirmed, but the amount of improvement for model fit is not answered by the *chi-square* test.

Table 3-11: Markov Assumption Tests

	Base	**Final Model**	**$LTCS_{prior}$ versus Base**	**$LTCS_{prior}$ versus Final Model**
	$LTCS_{now}$	$LTCS_{now}$ + S+ A+L	$LTCS_{now}$+ $LTCS_{prior}$	$LTCS_{now}$ + S+ A+L + $LTCS_{prior}$
Number of Estimations	20	50	36	70
Chi-square		234.93**	281.10**	251.32**

S: gender A: Age L: Living Arrangement
**: *P-value*≤0.01

The *chi-square* test is statistically significant due to the large volume of data included in this dissertation. This indicates that the impact of the immediate prior LTCS is not zero. However, in order to test the goodness of the model fit, a generalized liner regression is conducted. This dissertation uses the individual's expected capitation rate as a dependent variable. Based on the R squared values, including prior LTCS in the model increases the R square from 0.71 to 0.73, as shown in Table 3-12. However, this approach requires an additional 20 estimations ($LTCS_{now}$ + S+ A+L + $LTCS_{prior}$ versus $LTCS_{now}$ + S+ A+L) to improve the model fit by only 2%. Although including the immediate prior LTCS can improve the ability to predict future LTCS, the amount of improvement does not justified the added model complexity.

Table 3-12: Goodness of Model Fit

Predictors for $LTCS_{next}$	R-Square
$LTCS_{now}$	0.70
$LTCS_{now}$+S	0.70
$LTCS_{now}$+S+A	0.71
$LTCS_{now}$+S+A+L	0.71
$LTCS_{now}$+S+A+L+$LTCS_{prior}$	0.73

Chapter 4. **Validation**

The aim of this chapter is to validate the developed LTCS transition matrix. In order to validate the transition matrix, two research questions are tested:

a) Is the transition matrix externally valid?

b) Is the transition matrix internally valid?

These questions are investigated below.

For external validity, regardless of the transitions between capitation rate levels and living arrangements among individuals, comparing the closed cohort mortality projection with the published life table for the Social Security population estimated by the National Center for Health Statistics (NCHS) is a concise approach to test the external validity of the model. For internal validity, this research uses data from 2010 to 2011 to test internal validity by comparing the actual transition rate with the expected transition rate. The *chi-square* test is used to compare the actual and expected transition rates. The details are discussed below.

4.1. External Validity

The model construction process demonstrates that gender only has a statistically significant impact on individuals in the LTCS=A population; it does not enhance the ability to predict the future LTCS when an individual's LTCS is B, C, D, or E. This research uses the expected transition rate to project the future by gender of a closed cohort of 10,000 60-year-old individuals whose LTCS is A and who live at home alone. This population type is considered the lowest cost and most independent group among the target population in this research. The trends of this closed cohort for males and females are displayed in Figure 4-1 and Figure 4-2 separately.

The projected results are similar for females and males. Both closed cohorts are expected to disappear entirely at approximately the same time. Yet, the mortality results do not match the projections estimated by the NCHS. The female and male life expectancies estimated by NCHS suggest that women have a longer life expectancy at age 60.[73] NCHS indicates that males have 20.92 expected life years after age 60, while females have 23.97 years. Consequently, the results derived from the previous transition matrixes are not externally valid because they indicate almost the same life expectancies for both genders.

Even though the impact of gender on status changes is not statistically significant based on *chi-squared* tests for starting LTCS=B, C, D, and E, many previous studies have shown that gender has an impact on mortality rate, which is one of the possible ending statuses. This suggests that adding a gender effect on ending LTCS=Death is necessary. Thus, an additional estimation is used for starting LTCS=B, C, D and E. Once the gender effect is added, the *p-value* of its effect on ending LTCS=Death is less than 0.01, indicating that including the impact of gender only on ending LTCS=Death is both statistically and practically significant.

After refitting the model, the results suggest that overall females are less likely to die in any given starting LTCS than males. These results are consistent with previous studies.[3,73] Female and male mortalities are displayed in Figure 4-3, which compares the results with added gender impact and without gender impact. Including gender in the model differentiates mortality rates for the two genders.

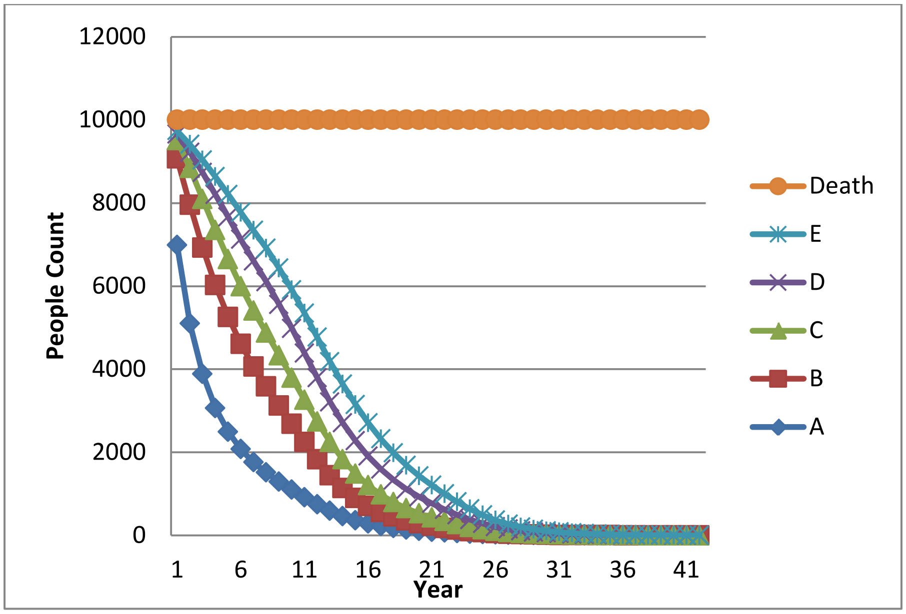

Figure 4-1: Analytical Projection--Female, Age: 60, LTCS=A, Living at Home Alone

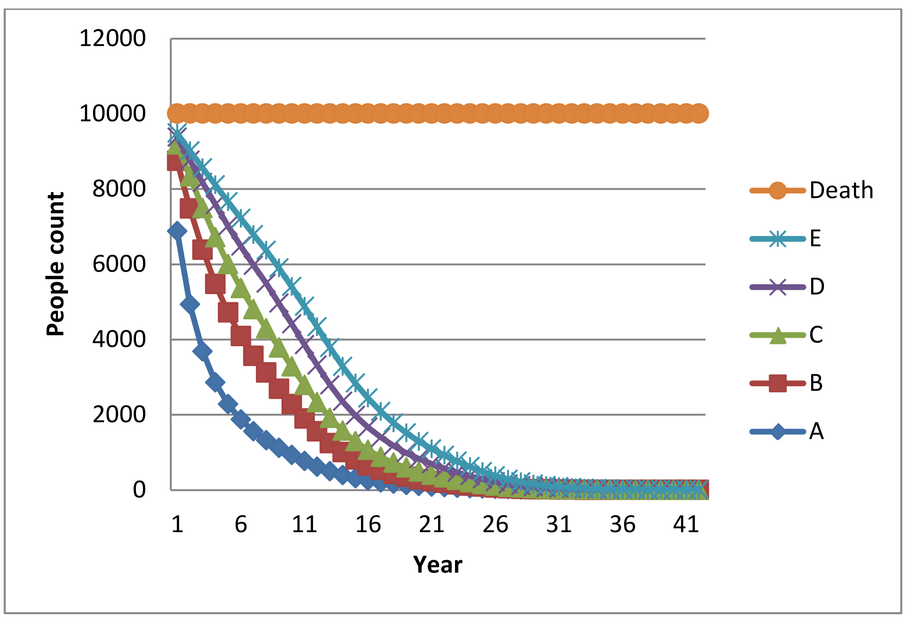

Figure 4-2: Analytical Projections--Male, Age: 60, LTCS=A, Living at Home Alone

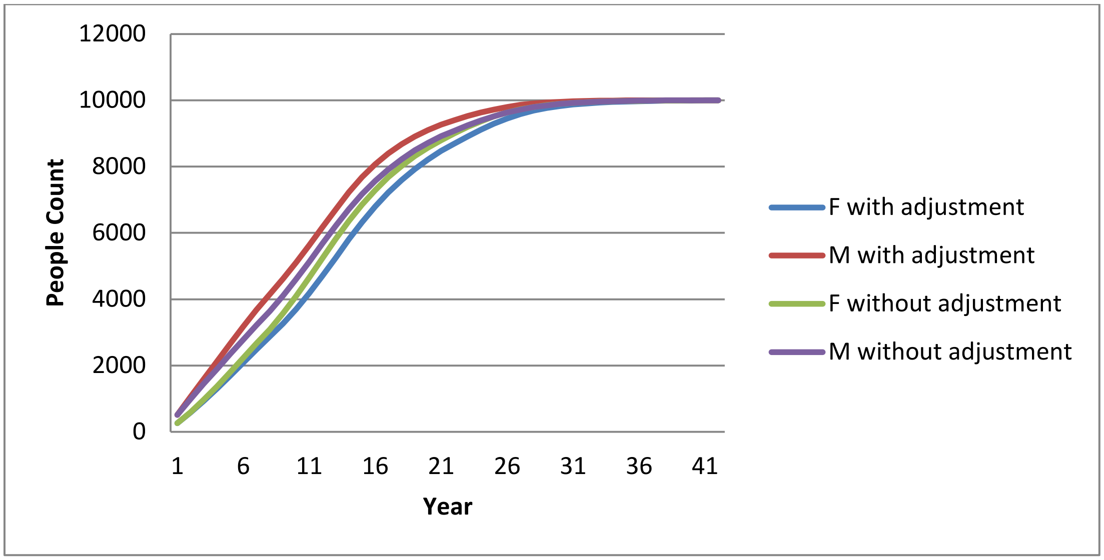

Figure 4-3: Total Mortality with and without gender impacts

4.2. Cross Validation

In order to evaluate the prediction performance of previously developed model, a cross-validation test using an additional year of data (2010-2011), denoted as the validation dataset, is applied. In brief, the data from 2008-2010 (denoted as the model construction dataset) are used to construct the LTCS transition model and estimate model parameters; these steps were described in Chapter 3. As the census dates chosen by this research for model construction dataset are June 30 in 2008, 2009, and 2010, an additional year of available data from July 1, 2010, to June 30, 2011, is examined. The most recent data are extracted on the census date in 2011, and are matched with 2010 data at the individual level.

In order to maintain the consistency of the data, the most updated functional screens for both 2010 and 2011 are used as a dataset to validate the developed model. Due to delayed system updating, we note that the new extract functional screen contains approximately 1,100 additional

Family Care elderly (>60) members records on Jun/30/2010 who did not appear in model construction dataset on Jun/30/2010. Thus, these 1,100 members are included in construction of the validation dataset; however, future research should anticipate the possible recurrence of this administrative issue.

An observed transition rate matrix is constructed from the validation dataset and is shown in Table 4-1 . We apply the developed model to the new 2010 starting population to obtain the expected transition rates, so an expected transition rate matrix is also constructed. The difference between the actual and expected transition rates is an indicator for evaluating model performance. Comparing the 2010-2011 actual transition rates and the expected transition rates estimated by the previous model directly is a preliminary approach to evaluate the developed model's performance. Table 4-1looks encouraging because actual transition rates seem close to expected transition rates. Among total 30 comparisons, only four cells show over 2% difference between actual and expected transition rates, and the biggest difference is for P(LTCS=C|LTCS=C) with 5.21% difference.

But, the evaluation of model prediction performance by starting LTCS, gender, age, and living situations is needed. Besides, the validation dataset is from the most updated functional screen, while the model construction data is from an older version. Therefore, this research conducts a sequence of cross-validation tests to evaluate the model's prediction performance. First, the consistency of the two datasets must be assessed. Second, we compare the actual transition rates distributions from the validation dataset to the maximum likelihood estimators of transition rates for the two datasets. For cross-validation procedures, see Hogg and Craig.[74] The details of each step are illustrated and discussed in 4.2.1 and 4.2.2.

Table 4-1: Comparison of actual and expected transition rate of validation dataset						
	Ending LTCS					
Starting LTCS	**A**	**B**	**C**	**D**	**E**	**Death**
A	63.75% (65.32%)	21.64% (20.06%)	4.17% (4.90%)	3.27% (2.39%)	1.39% (2.01%)	5.78% (5.32%)
B	9.85% (9.16%)	55.55% (55.41%)	17.79% (17.13%)	5.82% (7.27%)	2.94% (3.57%)	8.06% (7.48%)
C	0.78% (1.14%)	9.39% (9.46%)	51.84% (46.63%)	20.68% (24.81%)	6.71% (7.66%)	10.60% (10.31%)
D	0.44% (0.44%)	1.42% (1.51%)	10.00% (10.19%)	55.10% (51.62%)	18.91% (21.60%)	14.13% (14.66%)
E	0.03% (0.10%)	0.73% (0.57%)	0.96% (1.28%)	10.28% (9.99%)	64.03% (63.21%)	23.98% (24.88%)

First row in each cell is actual transition rate
Second row in each cell is expected transition rate

4.2.1. Model Construction Dataset versus Validation Dataset

The aim of this step is to evaluate whether the model construction dataset and the validation dataset share consistent status transition characteristics. There are 120 populations (i) (5 starting LTCS × 2 genders × 3 age levels × 4 living situations) and 120 sets of corresponding transition rates for both datasets (k=1,2). Each population also has six response outcomes (j=1,2,……6). Each population i has N_i^k individuals in the k^{th} dataset, and the population i has N_{ij}^k individuals ending in status j in the dataset k. There are two independent multinomial distributions with parameters N_i^k, $P_{1.}^{k}$, $P_{2.}^{k}$, $P_{3.}^{k}$,…, $P_{120.}^{k}$, k=1, 2, respectively. This approach tests the hypothesis that multinomial distribution of transition rates from population i based on the model construction dataset ($P_{i.}^{1}$) is equal to the multinomial distribution of transition rates from population i based on the validation dataset ($P_{i.}^{2}$). Our null hypothesis is that

$$H_0: P_i^1 = P_i^2 = P_i^0 \text{ as } i=1, 2 \ldots\ldots 120$$

Under the local null hypothesis of equal transition probabilities, the maximum likelihood estimator of P_i^0, based upon the joint frequency of ij from both datasets, is given by $(N_{ij}^1 + N_{ij}^2)/(N_i^1 + N_i^2)$, i=1, 2 ……120.

The random variables

$$Q_i = \sum_{k=1}^{2} \sum_{j=A}^{Death} \frac{\left(N_{ij}^k - N_i^k\left((N_{ij}^1 + N_{ij}^2)/(N_i^1 + N_i^2)\right)\right)^2}{N_i^k\left((N_{ij}^1 + N_{ij}^2)/(N_i^1 + N_i^2)\right)} \text{ as } i=1,2,3,\ldots\ldots,120$$

have approximate X^2 distributions each with 2j-2-(j-1)=j-1 degrees of freedom. Thus, we can test the hypothesis that the two multinomial distributions from model construction dataset and validation dataset are the same for each population.

The X^2 and *p-value* distributions are shown in Appendix B. This research examines the X^2 statistic Q for each population i and identifies populations with significant *p-values* (<0.05). The null hypothesis of dataset equality is rejected in nine populations:

(1) LTCS=A, female, 73-85, home alone;

(2) LTCS=C, female, >85, home with a helper;

(3) LTCS=C, female, >85, community assisted living;

(4) LTCS=C, male, >85, community assisted living;

(5) LTCS=D, female, 60-72, home alone;

(6) LTCS=D, female, >85, home with a helper;

(7) LTCS=D, male, 60-72, living at home with a helper;

(8) LTCS=E, male, 60-72, home with a helper;

(9) LTCS=E, male, 60-72, nursing home.

In addition, the population LTCS=A, male, >85, nursing home has no observations in validation dataset ($N_{i.}^{2}$=0), so we exclude this population from the total comparison. Therefore, the total number of populations is 119 (120-1).

If the multinomial distribution of actual transition rates for the two datasets (k=1, 2) are the same at all populations of a global null hypothesis, the 5.95 comparisons/populations would be expected to reject the null hypothesis at the 5% significance level. Therefore, the probability of having at least nine (x>8) locally rejected populations among 119 trails with 0.05 failure rate is 0.14 follwoing by binomial distribution.

$$1 - \sum_{x=0}^{8} \binom{n}{x} p^{x} (1-p)^{n-x} = 0.14$$

The critical value of rejecting the consistency between two datasets is 11 at a 5% significance level, which means 11 populations/comparisons rejecting null hypothesis. Thus, the global hypothesis cannot be rejected, and the consistency between two datasets is plausible.

4.2.2. Actual Transition Rate from Validation Dataset versus Expected Transition Rate from Developed Model

The aim of this step is to compare the consistency of actual transition rates distributions from the validation dataset and expected transition rates derived from the developed model at all population (i). Previous test shows that consistency between the validation dataset and the model construction dataset is plausible at a 5% significance level. Testing P_i^2 and $\widehat{\pi_i}$ directly is not a suitable approach for model validation, because $\widehat{\pi_i}$ is not the true transition rates distribution (π_i) but it reflects the same aggregation in populations used in the model development. This research uses the model construction dataset's expected multinomial distributions for each population i $\widehat{\pi_i}$ to replace π_i. This is an appropriate approach to validate model by testing if the transition rates distributions for P_i^2 and π_i are the same[74]. Our null hypothesis is

$$H_0: P_i^2 = \pi_i = p_i^0 \text{ where } i=1,2,\ldots, 120$$

Under the local null hypothesis of equal transition probabilities, the maximum likelihood estimator of p_i^0 based upon the joint frequencies N_{ij} is $\frac{N_{ij}^2+N_i^1\times\widehat{\pi_{ij}}}{N_i^2+N_i^1}$ which blends two datasets.

As above, the random variables

$$Q_i=\sum_{k=1}^{2}\sum_{j=A}^{Death}\frac{\left(N_{ij}^k-N_i^k\times\left(\frac{N_{ij}^2+N_i^1\times\widehat{\pi_{ij}}}{N_i^2+N_i^1}\right)\right)^2}{N_i^k\times\left(\frac{N_{ij}^2+N_i^1\times\widehat{\pi_{ij}}}{N_i^2+N_i^1}\right)} \sim X^2_{(5)} \text{ i=1,2,......120}$$

have approximately X^2 distributions each with j-1=5 degrees of freedom.

The *p-values* of the X^2 results are shown in Table 4-2. The results suggest that seven populations:

(1) LTCS=A, female, 60-72, home alone;

(2) LTCS=B, male, 60-72, home alone;

(3) LTCS=B, male, 60-72, home with a helper;

(4)LTCS=B, male, 60-72, community assisted living;

(5) LTCS=B, male, 60-72, nursing home;

(6) LTCS=C, female, >85, community assisted living;

(7) LTCS=E, male, 60-72, nursing home

are significantly different at a 5% significance level. In addition, population LTCS=A, male, >85, nursing home has no observations (N_i^1=0) in validation dataset. Therefore, the total number of populations is 119 (120-1). 5% of total 119 populations (5.95) would be expected to appear to reject null hypothesis at a 5% significance level.

The probability of have at least seven (x>6) locally rejected population among 119 trails with 0.05 failure rate is 0.38 following by binomial distribution.

$$1 - \sum_{x=0}^{6} \binom{n}{x} p^x (1-p)^{n-x} = 0.38$$

Therefore, although there are 7 populations with different multinomial distributions locally, is the global null hypothesis cannot be reject since the critical value is 11.So the validity of model prediction performance is plausible and valuable to illustrate the possible changes in population LTC cost level structure and corresponding future applications.

Table 4-2: Comparing actual transition rate from validation data and expected transition rate from model construction dataset with joint transition rate

i	Starting LTCS	Gender	Age	Living Situation	Q	p-value
1	A	F	A	HA	11.69	0.04
2	A	F	A	H	2.75	0.74
3	A	F	A	C	1.77	0.88
4	A	F	A	I	3.36	0.65
5	A	F	B	HA	7.05	0.22
6	A	F	B	H	11.23	0.05
7	A	F	B	C	1.76	0.88
8	A	F	B	I	2.64	0.76
9	A	F	C	HA	2.64	0.75
10	A	F	C	H	6.50	0.26
11	A	F	C	C	6.28	0.28
12	A	F	C	I	1.51	0.91
13	A	M	A	HA	4.40	0.49
14	A	M	A	H	7.30	0.20
15	A	M	A	C	4.03	0.54
16	A	M	A	I	1.79	0.88
17	A	M	B	HA	2.17	0.82
18	A	M	B	H	3.69	0.59
19	A	M	B	C	2.39	0.79
20	A	M	B	I	1.53	0.91
21	A	M	C	HA	3.22	0.67
22	A	M	C	H	3.25	0.66
23	A	M	C	C	4.07	0.54
24	A	M	C	I	NA	NA
25	B	F	A	HA	3.85	0.57
26	B	F	A	H	10.15	0.07
27	B	F	A	C	3.46	0.63
28	B	F	A	I	7.87	0.16
29	B	F	B	HA	2.27	0.81
30	B	F	B	H	4.70	0.45
31	B	F	B	C	4.38	0.50
32	B	F	B	I	1.12	0.95
33	B	F	C	HA	0.39	1.00

34	B	F	C	H	1.70	0.89
35	B	F	C	C	2.37	0.80
36	B	F	C	I	1.92	0.86
37	B	M	A	HA	112.24	0.00
38	B	M	A	H	11.77	0.04
39	B	M	A	C	107.52	0.00
40	B	M	A	I	16.71	0.01
41	B	M	B	HA	3.27	0.66
42	B	M	B	H	2.56	0.77
43	B	M	B	C	1.86	0.87
44	B	M	B	I	1.26	0.94
45	B	M	C	HA	2.47	0.78
46	B	M	C	H	5.05	0.41
47	B	M	C	C	0.79	0.98
48	B	M	C	I	2.12	0.83
49	C	F	A	HA	7.30	0.20
50	C	F	A	H	4.52	0.48
51	C	F	A	C	7.22	0.20
52	C	F	A	I	0.92	0.97
53	C	F	B	HA	4.53	0.48
54	C	F	B	H	7.09	0.21
55	C	F	B	C	9.16	0.10
56	C	F	B	I	6.94	0.23
57	C	F	C	HA	2.92	0.71
58	C	F	C	H	4.16	0.53
59	C	F	C	C	16.08	0.01
60	C	F	C	I	4.30	0.51
61	C	M	A	HA	8.49	0.13
62	C	M	A	H	5.04	0.41
63	C	M	A	C	8.08	0.15
64	C	M	A	I	4.75	0.45
65	C	M	B	HA	3.54	0.62
66	C	M	B	H	3.41	0.64
67	C	M	B	C	4.89	0.43
68	C	M	B	I	0.81	0.98
69	C	M	C	HA	1.43	0.92
70	C	M	C	H	2.01	0.85
71	C	M	C	C	5.05	0.41
72	C	M	C	I	1.62	0.90
73	D	F	A	HA	6.00	0.31
74	D	F	A	H	3.02	0.70
75	D	F	A	C	6.46	0.26

76	D	F	A	I	6.33	0.28
77	D	F	B	HA	6.22	0.29
78	D	F	B	H	1.26	0.94
79	D	F	B	C	4.24	0.51
80	D	F	B	I	2.98	0.70
81	D	F	C	HA	2.88	0.72
82	D	F	C	H	7.38	0.19
83	D	F	C	C	4.33	0.50
84	D	F	C	I	4.15	0.53
85	D	M	A	HA	5.80	0.33
86	D	M	A	H	7.91	0.16
87	D	M	A	C	10.41	0.06
88	D	M	A	I	1.37	0.93
89	D	M	B	HA	8.79	0.12
90	D	M	B	H	4.54	0.47
91	D	M	B	C	6.69	0.24
92	D	M	B	I	1.51	0.91
93	D	M	C	HA	2.76	0.74
94	D	M	C	H	1.86	0.87
95	D	M	C	C	3.27	0.51
96	D	M	C	I	4.46	0.49
97	E	F	A	HA	2.10	0.84
98	E	F	A	H	6.30	0.28
99	E	F	A	C	1.21	0.94
100	E	F	A	I	6.97	0.22
101	E	F	B	HA	0.37	1.00
102	E	F	B	H	2.70	0.75
103	E	F	B	C	2.99	0.70
104	E	F	B	I	2.06	0.84
105	E	F	C	HA	3.41	0.64
106	E	F	C	H	1.52	0.91
107	E	F	C	C	4.62	0.46
108	E	F	C	I	0.64	0.99
109	E	M	A	HA	6.06	0.30
110	E	M	A	H	10.35	0.07
111	E	M	A	C	7.06	0.13
112	E	M	A	I	12.29	0.03
113	E	M	B	HA	1.09	0.95
114	E	M	B	H	4.76	0.45
115	E	M	B	C	3.68	0.45
116	E	M	B	I	3.22	0.67
117	E	M	C	HA	1.89	0.86

118	E	M	C	H	1.34	0.85
119	E	M	C	C	0.90	0.93
120	E	M	C	I	2.10	0.83

4.3. Conclusion

The three statistical tests described above evaluated both the external validity and prediction performance of the developed model. The gender impact is added back to each population on the death outcome only; therefore, additional estimations are needed. This adjustment allows the developed model to meet external validity based on published studies. For the prediction performance of the developed model, cross-validation *chi-square* tests were applied to each step of the modeling process.

Although the result shows 9 populations with different distributions, the hypothesis of the consistency between the validation data and the model construction data cannot be rejected. Because the frequency of populations with different distributions follows the binomial distribution, the critical value of rejecting hypothesis is 11 based on 119 trials and 5% mean probability. Thus the validation dataset can provide valuable information on the model validation process.

Even though 7 populations with different multinomial distributions between validation dataset and expected dataset derived from developed model, the null hypothesis of $P_i^2 = \hat{\pi}_i$ is not rejected since the critical value of rejecting hypothesis is 11 as discussed previously. Therefore, the prediction performance of developed model is valid, thus the model provide valuable information on transition rates for future research directions. .

Chapter 5. **Results**

5.1. Observed Long Term Care Status Transition Rate

Given the current LTCS, the probabilities of moving to the next LTCS are constructed, and the results are shown in Table 5-1. The probability of remaining at the same status declines from starting LTCS=A to LTCS=C, but it increases from starting LTCS=C to LTCS=D. The improvement probabilities decline when the starting LTCS is more impaired; at the same time, the impairment probabilities increase. The mortality rate increases from 5 % to 26 % from starting LTCS=A to LTCS=E. According to the ending statuses, most of the population migrates toward more impaired statuses after one year; the percentages of LTCS=A, B, and C in the total population decline among those who are still alive after one year. The percentages of more impaired statuses increase over a year. The average monthly expected cost also increases from $2,182 to $2,268 per person.

The observed transition rate table is stratified by age into three levels: 60-72, 73-85, and 85+. The stratified results are shown in Table 5-2. The probability of staying in the same LTCS after one year declines when the age increases given the same starting LTCS. In addition, the mortality rate increases when the age increases given the same starting LTCS. The older population is more likely to get more impaired, and the younger population is more likely to recover given the same starting and ending LTCS.

The observed transition rate matrix stratified by gender is displayed in Table 3-2 and Table 3-3. It suggests that males have a higher mortality rate across all starting LTCS without adjusting by other factors. But males are less likely to deteriorate than females given starting

LTCS=B, C, D and E. The stratified results show the differences among age groups and between genders. Therefore, the fitted results can explain the impact from these independent variables.

Table 5-1: Fully Observed Transition Rate with Average Expected Cost

	Ending LTCS						
Starting LTCS (Ave Cost)	**A**	**B**	**C**	**D**	**E**	**Death**	**Total**
A ($891)	2202 (66.3%)	660 (19.9%)	156 (4.7%)	76 (2.3%)	59 (1.8%)	166 (5.0%)	3319 (14.9%)*
B ($1,360)	469 (9.9%)	2730 (57.8%)	739 (15.6%)	310 (6.6%)	156 (3.3%)	323 (6.8%)	4727 (21.2%)*
C ($1,958)	60 (1.4%)	493 (11.3%)	2077 (47.6%)	999 (22.9%)	309 (7.1%)	429 (9.8%)	4367 (19.6%)*
D ($2,633)	21 (0.4%)	84 (1.7%)	548 (10.8%)	2688 (52.9%)	1050 (20.6%)	694 (13.6%)	5085 (22.8%)*
E ($3,627)	5 (0.1%)	29 (0.6%)	65 (1.4%)	466 (9.7%)	3002 (62.6%)	1225 (25.6%)	4792 (21.5%)*
Total	**2757 (14.2%)****	**3996 (20.5%)****	**3585 (18.4%)****	**4539 (23.3%)****	**4576 (23.5%)****	**2837**	**22290 ($2,182)+ ($2,268)+**

* Percentage of total sample size
** Percentage of total sample size minus death population
\+ Average monthly cost in starting year

Table 5-2: Observed Transition Rate by Age

	Ending LTCS					
Starting LTCS	**A**	**B**	**C**	**D**	**E**	**Death**
LTCS=A						
60-72	68.9%	20.5%	4.5%	1.6%	1.0%	3.5%
73-85	65.4%	19.8%	4.6%	2.7%	1.7%	5.7%
>85	59.2%	17.7%	5.7%	3.8%	5.0%	8.7%
LTCS=B						
60-72	11.3%	62.1%	14.8%	5.2%	2.5%	4.1%
73-85	9.5%	57.8%	15.5%	6.4%	3.4%	7.4%
>85	7.1%	45.5%	18.1%	10.9%	5.4%	13.1%
LTCS=C						
60-72	2.0%	14.9%	50.9%	22.0%	4.3%	5.9%
73-85	1.3%	10.4%	48.7%	22.6%	7.7%	9.2%
>85	0.5%	6.9%	40.2%	24.8%	10.5%	17.2%
LTCS=D						
60-72	0.7%	2.3%	13.6%	58.9%	17.0%	7.5%
73-85	0.3%	1.7%	9.6%	52.4%	21.7%	14.2%
>85	0.2%	0.7%	8.7%	45.6%	23.9%	20.9%
LTCS=E						
60-72	0.2%	1.0%	1.4%	14.1%	68.3%	15.0%
73-85	0.0%	0.7%	1.6%	9.0%	64.4%	24.3%
>85	0.2%	0.2%	1.0%	6.9%	55.7%	36.0%

5.2. Long Term Care Status Transition Matrix

Each estimated value, odd ratios (OR), represents the impact of the independent variable on the indicated ending status compared to the reference status (i.e., no change in status), given that only these two outcomes are possible. Starting LTCS=A or E require more complex parametric forms than other starting LTCS. Both have interaction effects between age and living situation but only for the community assisted living or nursing home populations. There is no additional adjustment required for living at home with a helper compared to living at home alone when the starting LTCS is either A or B. The difference between living at home with helpers and living at home alone occurs when individuals are more dependent at the start. The details for each starting status are discussed in the following sections.

LTCS=A

The final fitted model for LTCS=A needs 32 parameters to explain the variation of ending LTCS among individuals. The additional adjustment is needed by gender throughout all possible LTCS transitions, age older than 72, age older than 85, and living at community assisted living or nursing homes. No additional adjustment is required for those who live in nursing homes. The effect of living in a nursing home is equal to the effect of living in community assisted living.

Compared to the male population, the female population is less likely to deteriorate, and females are also less likely to die (OR=0.5) after one year than remaining at LTCS=A. The probability of worsening increases as age increases. Individuals who are older than 85 are more likely to get more impaired compared to the age level A (60-72) population than remaining at LTCS=A. Although the oldest group has approximately three times the risk of dying (OR=3.11) compared to the youngest group (60-72), the total mortality for starting LTCS=A is only 5%, as shown in Table 5-3 Therefore, the number of individuals under this impact is relatively small.

Table 5-3:Multinomial Regression of Transitions in LTCS=A

	Ending Status					
Starting LTCS=A	A vs. A	B vs. A	C vs. A	D vs. A	E vs. A	Death vs. A
Intercept	-	0.27	0.06	0.03	0.02	0.08
Gender (ref: male)						
Female	-	1.10	0.99	0.73	0.73	0.50
Age (ref: 60-72)						
Age:73-85	-	0.99	1.03	1.86	1.98	1.91
Age:>85	-	1.03	1.53	3.03	6.08	3.11
Living Arrangement (ref: HA)						
Live:>=C	-	7.03	10.62	10.62	22.48	13.07
Interaction (ref: 60-72×HA)						
Age:73-85×Live:>=C	-	0.63	0.59	0.20	0.20	0.07
Age:>85×Live:>=C	-	0.19	0.12	0.50	0.50	2.36

Individuals living in either community assisted living or nursing homes have a higher risk of deteriorating in the following year compared to those who stay at home regardless of whether they live alone or with helpers. The interaction between age and living situation also adjusts the transition probabilities. The probability of impairment is higher before adding the interaction adjustment, especially for those who migrate to LTCS=D or LTCS=E. Using the interaction adjustment makes the OR patterns smoother. This result makes sense not only statistically but also clinically. For example, those who are least ill at the start of the study, LTCS=A, and living at community assisted living receive more medical attention; therefore, the risk of death is lower after interaction adjustment.

The results in Table 5-3 are Odd Ratios (OR). The following paragraph demonstrates how to calculate the transition rate from OR provided in Table 5-3. This example uses the following parameters: Female, age 78, living in community assisted living, ending LTCS=C.

$$P_{AC}=\frac{OR_{j=C}{}^{female,78,community}}{\sum_{j=A}^{j=Death} OR^{female,78,community}}=$$

$$\frac{(0.06\times0.99\times1.03\times10.62\times0.59)}{1+(0.27\times1.10\times0.99\times7.03\times0.63)+(0.06\times0.99\times1.03\times10.62\times0.59)+(0.03\times0.73\times1.86\times10.62\times0.2)+(0.02\times0.73\times1.98\times22.48\times0.2)+(0.08\times0.5\times1.91\times13.07\times0.7)}$$

$$=15\%$$

LTCS=B

21 parameters are required to model the ending LTCS given starting LTCS=B after the aggregation and simplification process, and adding gender effect back only on ending LTCS=Death. The results are displayed in Table 5-4. In the population that remains in the same LTCS (LTCS=B) after one year, females are less likely to die compared to males (OR=0.75).

The current living situation is divided into two levels: residing in community assisted living or nursing home, and living at home either with or without a caregiver. The effect of living at home with a helper is as the same as the effect of living at home alone. No additional adjustment is added for those who live in nursing homes, which means the effects of living in community assisted living and nursing homes are equivalent. Among those who remain in LTCS=B (no change), community assisted living or nursing home residents are less likely (OR=0.61) to recover from current LTCS compared to those who live at home; they are more likely to deteriorate or die.

For improvement, the estimations suggest that age does not make a notable difference, but age groups B (73-85) and C (>85) are slightly less likely to recover compared to the youngest age group; on the other hand, both populations are more likely to deteriorate compared to the youngest age group. The >85 population has more than 4 times the risk (OR=4.27) of death than the youngest population over a year. Individuals living in community assisted living or nursing homes are less likely to improve from current LTCS (OR=0.61), and they have higher risk of impairment and death (OR=1.8).

Table 5-4:Multinomial Regression of Transitions in LTCS=B

	Ending Status					
Starting LTCS=B	A vs. B	B vs. B	C vs. B	D vs. B	E vs. B	Death vs. B
Intercept	0.19	-	0.22	0.08	0.04	0.08
Gender (ref: male)						
Female	-	-	-	-	-	0.75
Age (ref: 60-72)						
Age:73-85	0.91	-	1.10	1.31	1.45	1.95
Age:>85	0.89	-	1.45	2.55	2.70	4.27

Living Arrangement (ref: HA&H)						
Live:>=C	0.61	-	2.54	2.33	1.96	1.80

LTCS=C

This model uses 73+, >85, home without helper, community assisted living, and nursing home as independent variables, and it needs total 31 parameters (shown in Table 3-9) to model the transition rates. Table 5-5 describes the estimated MLML results. Age still appears to have a similar impact on migration patterns for both the 73-85 and >85 populations, and compared to the youngest age group, ages 73-85 and ages >85 are less likely to recover from current status compared to youngest age population. In addition, 85+ recipients are more likely to move to status E (OR=2.99) compared to the youngest age group than staying at LTCS=C over a year, and the >85 group also has a higher risk of death (OR=4.10).

Those who live at home with a caregiver or in community assisted living are less likely to improve from their current LTCS; however, nursing home residents are more likely to recover to LTCS=A than remain the same LTCS compared to those who live at home alone. Yet, this result does not imply that the probability of moving to LTCS=A from LTCS=C is absolutely high. However, overall those who live in nursing homes are more likely to deteriorate compared to those who live at home alone as well.

This study observes that living in community assisted living compared to living at home alone has a lower risk of mortality rate (OR=0.83), which is approximately the same as living at home with helpers (OR=0.81). Although an individual living at home alone is considered functionally independent, the risk of mortality is not necessarily lower due to the nature of the starting LTCS. Overall, LTCS=C has a 9.8% mortality rate, as shown in Table 5-1. This finding shows that living with a helper can effectively reduce the mortality rate for the LTCS=C population.

Table 5-5:Multinomial Regression of Transitions in LTCS=C

	End Status					
Starting LTCS=C	A vs. C	B vs. C	C vs. C	D vs. C	E vs. C	Death vs. C
Intercept	0.07	0.51	-	0.33	0.07	0.17
Gender (ref: male)						
Female	-	-	-	-	-	0.68
Age (ref: 60-72)						
Age:73-85	0.69	0.73	-	1.06	1.86	1.67
Age:>85	0.41	0.70	-	1.27	2.99	4.10
Living Arrangement (ref: HA)						
Live: H	0.47	0.56	-	1.08	1.28	0.81
Live: C	0.08	0.22	-	1.78	1.49	0.83
Live: I	1.75	0.56	-	2.69	2.45	1.37

LTCS=D

The parametric form for starting LTCS=D is similar to LTCS=C, and it also requires 31 parameters to model the transition rates. Overall, females are less likely to die after one year compared to males (OR=0.67). For age, an additional adjustment is added for individuals older than 72, followed by another adjustment for individuals older than 85. The impacts of living arrangements are different among these 4 levels, and additional adjustment is needed for each level. Overall, the patterns among all these variables remain the same as starting LTCS=C. There is no significant difference in mortality rates between living at home with a helper (OR=0.66) and community assisted living (OR=0.67) compared to living at home alone; both are less likely to die after one year. Therefore, the previous finding—that living at home with a helper effectively reduces the mortality rate—is supported.

In addition, individuals living in nursing homes have a higher chance of improving three levels (from D to A (OR=2.09)), compared to the reference living group (living at home alone), but also have a higher risk of death (OR=1.25) compared to individuals living at home alone. Recipients living in community assisted living have the smallest chance of improvement. People with starting LTCS=D, which is a relatively severe status, living in nursing homes are more likely to recover from their current status to LTCS=A compared those who are not admitted to institutional care. However, based on Table 5-6, only 0.4% of individuals in the starting LTCS=D population are transitioning from LTCS=D to LTCS=A.

Table 5-6:Multinomial Regression of Transitions in LTCS=D						
	End Status					
Starting LTCS=D	A	B	C	D	E	Death
Intercept	0.04	0.15	0.41	-	0.19	0.21
Gender (ref: male)						
Female	-	-	-	-	-	0.67
Age (ref: 60-72)						
Age:73-85	0.45	0.85	0.80	-	1.40	2.25
Age:>85	0.42	0.46	0.86	-	1.77	4.03
Living Arrangement (ref: HA)						
Live: H	0.19	0.22	0.62	-	1.48	0.66
Live: C	0.06	0.09	0.45	-	1.49	0.67
Live: I	2.09	0.66	0.62	-	2.54	1.25

LTCS=E

The parametric form uses 38 parameters to model the transition rate among individuals whose starting LTCS=E. This model includes gender, ages 73-85, ages >85, home alone, community assisted living, and nursing home as independent variables (shown in Table 5-7). In addition, it includes an interaction term between age levels and current living situations. Overall, compared to the youngest age group (60-72), both the 73-85 and >85 populations are less likely to improve from LTCS=E, and have higher risks of death. Recipients >85 are more likely to die compared to the youngest age group recipients (OR=2.17). Recipients living with helpers (either skilled medical professionals or informal care givers) are less likely to pass away compared to those living alone; this is supported by previous findings that when the starting LTCS is more impaired, living with caregivers can effectively reduce the risk of death.

Table 5-7:Multinomial Regression of Transitions in LTCS=E						
	End Status					
Starting LTCS=E	A	B	C	D	E	Death
Intercept	0.03	0.17	0.16	0.45	-	0.45
Gender (ref: male)						
Female	-	-	-	-	-	0.72
Age (ref: 60-72)						
Age:73-85	0.24	0.24	0.56	0.61	-	1.15
Age:>85	0.21	0.21	0.51	0.57	-	2.38
Living Arrangement (ref: HA)						
Live: H	0.11	0.11	0.21	0.57	-	0.64
Live: C	0.01	0.01	0.05	0.42	-	0.38
Live: I	0.07	0.07	0.07	0.35	-	0.86
Interaction (ref: 60-72×HA)						
Age:73-85×Live: C	3.17	3.17	3.17	1.71	-	2.32
Age:73-85×Live: I	5.33	5.33	5.33	0.74	-	1.38
Age:>85×Live: I	3.45	3.45	3.45	0.65	-	0.93

The fitted transition rate matrix is constructed after converting log OR into probabilities. The transition rates of given starting LTCS, age levels, and living arrangements are presented in Table 5-8 and Table 5-9 by gender.

Table 5-8: Comprehensive Transition Rate Matrix--Female

			Ending Status					
			A	**B**	**C**	**D**	**E**	**Death**
Starting LTCS	**Age**	**Living Situation**						
A								
	60-72							
		HA	69.8%	20.9%	4.4%	1.4%	0.8%	2.6%
		H	69.8%	20.9%	4.4%	1.4%	0.8%	2.6%
		C	21.0%	44.2%	15.7%	3.7%	5.1%	10.3%
		I	21.0%	44.2%	15.7%	3.7%	5.1%	10.3%
	73-85							
		HA	66.9%	19.8%	4.4%	2.5%	1.6%	4.8%
		H	66.9%	19.8%	4.4%	2.5%	1.6%	4.8%
		C	33.4%	43.9%	15.1%	2.2%	3.2%	2.2%
		I	33.4%	43.9%	15.1%	2.2%	3.2%	2.2%
	>85							
		HA	60.4%	18.6%	5.9%	3.7%	4.4%	7.1%
		H	60.4%	18.6%	5.9%	3.7%	4.4%	7.1%
		C	55.8%	14.1%	4.7%	3.0%	8.1%	14.3%
		I	55.8%	14.1%	4.7%	3.0%	8.1%	14.3%
B								
	60-72							
		HA	11.8%	63.4%	13.9%	4.9%	2.4%	3.7%
		H	11.8%	63.4%	13.9%	4.9%	2.4%	3.7%
		C	5.6%	49.3%	27.6%	8.9%	3.7%	5.1%
		I	5.6%	49.3%	27.6%	8.9%	3.7%	5.1%
	73-85							
		HA	10.1%	59.6%	14.4%	6.0%	3.3%	6.7%
		H	10.1%	59.6%	14.4%	6.0%	3.3%	6.7%
		C	4.6%	44.2%	27.2%	10.4%	4.8%	8.9%
		I	4.6%	44.2%	27.2%	10.4%	4.8%	8.9%
	>85							
		HA	8.2%	49.3%	15.7%	9.7%	5.0%	12.1%
		H	8.2%	49.3%	15.7%	9.7%	5.0%	12.1%

		C	3.4%	33.2%	26.9%	15.2%	6.7%	14.7%
		I	3.4%	33.2%	26.9%	15.2%	6.7%	14.7%
C								
	60-72							
		HA	3.5%	24.3%	47.7%	15.9%	3.1%	5.4%
		H	1.9%	15.5%	53.9%	19.4%	4.5%	4.9%
		C	0.3%	5.8%	52.7%	31.2%	5.1%	4.9%
		I	4.9%	10.9%	38.1%	34.2%	6.1%	5.9%
	73-85							
		HA	2.5%	17.8%	48.0%	16.9%	5.8%	9.1%
		H	1.3%	10.9%	52.0%	19.8%	8.1%	7.9%
		C	0.2%	3.9%	48.8%	30.6%	8.8%	7.6%
		I	3.2%	7.4%	35.7%	33.9%	10.6%	9.3%
	>85							
		HA	1.2%	14.5%	40.5%	17.2%	7.9%	18.7%
		H	0.6%	8.8%	43.5%	20.0%	10.9%	16.3%
		C	0.1%	3.1%	39.9%	30.2%	11.5%	15.3%
		I	1.5%	5.7%	28.5%	32.6%	13.5%	18.1%
D								
	60-72							
		HA	1.9%	7.7%	21.1%	51.9%	10.0%	7.4%
		H	0.4%	2.0%	15.1%	59.8%	17.1%	5.7%
		C	0.1%	0.8%	11.4%	63.3%	18.2%	6.1%
		I	3.7%	4.7%	12.0%	47.7%	23.4%	8.5%
	73-85							
		HA	0.8%	6.1%	15.8%	48.5%	13.1%	15.6%
		H	0.2%	1.5%	10.9%	54.1%	21.7%	11.6%
		C	0.1%	0.6%	8.1%	56.2%	22.7%	12.2%
		I	1.4%	3.5%	8.4%	41.5%	28.5%	16.7%
	>85							
		HA	0.7%	2.9%	14.8%	42.6%	14.5%	24.5%
		H	0.1%	0.7%	10.2%	47.1%	23.8%	18.0%
		C	0.0%	0.3%	7.5%	48.5%	24.8%	18.9%
		I	1.1%	1.6%	7.5%	34.7%	30.1%	25.0%
E								
	60-72							
		HA	1.4%	8.0%	7.5%	21.3%	46.9%	15.0%
		H	0.2%	1.3%	2.2%	17.1%	65.9%	13.4%
		C	0.0%	0.1%	0.6%	14.3%	75.7%	9.2%
		I	0.1%	0.8%	0.8%	10.8%	68.7%	18.8%
	73-85							
		HA	0.4%	2.3%	5.0%	15.6%	56.1%	20.6%
		H	0.1%	0.3%	1.3%	11.2%	70.6%	16.5%

		C	0.0%	0.1%	0.9%	12.9%	65.0%	21.2%
		I	0.2%	1.0%	2.2%	4.6%	64.2%	27.9%
	>85							
		HA	0.3%	1.7%	3.8%	12.1%	46.6%	35.5%
		H	0.0%	0.3%	1.0%	9.0%	60.4%	29.2%
		C	0.0%	0.1%	0.7%	9.9%	53.4%	36.0%
		I	0.1%	0.5%	1.2%	3.5%	59.0%	35.8%

Table 5-9:Comprehensive Transition Rate Matrix--Male

			Ending Status					
			A	**B**	**C**	**D**	**E**	**Deat h**
Starting LTCS	**Age**	**Living Arrangement**						
A								
	60-72							
		HA	68.8%	18.7%	4.4%	1.9%	1.1%	5.2%
		H	68.8%	18.7%	4.4%	1.9%	1.1%	5.2%
		C	19.2%	36.6%	14.4%	4.6%	6.3%	18.8%
		I	19.2%	36.6%	14.4%	4.6%	6.3%	18.8%
	73-85	HA	64.0%	17.2%	4.2%	3.3%	2.1%	9.2%
		H	64.0%	17.2%	4.2%	3.3%	2.1%	9.2%
		C	33.3%	39.8%	15.2%	3.0%	4.3%	4.4%
		I	33.3%	39.8%	15.2%	3.0%	4.3%	4.4%
	>85	HA	55.7%	15.6%	5.4%	4.7%	5.5%	13.0%
		H	55.7%	15.6%	5.4%	4.7%	5.5%	13.0%
		C	47.7%	11.0%	4.0%	3.5%	9.5%	24.4%
		I	47.7%	11.0%	4.0%	3.5%	9.5%	24.4%
B								
	60-72							
		HA	11.7%	63.1%	13.9%	4.9%	4.0%	2.4%
		H	11.7%	63.1%	13.9%	4.9%	4.0%	2.4%
		C	5.6%	49.0%	27.4%	8.8%	5.6%	3.7%
		I	5.6%	49.0%	27.4%	8.8%	5.6%	3.7%
	73-85							

		HA	10.0%	59.3%	14.3%	6.0%	7.2%	3.3%
		H	10.0%	59.3%	14.3%	6.0%	7.2%	3.3%
		C	4.5%	43.9%	27.0%	10.3%	9.6%	4.7%
		I	4.5%	43.9%	27.0%	10.3%	9.6%	4.7%
	>85							
		HA	8.1%	49.0%	15.6%	9.7%	12.5%	5.0%
		H	8.1%	49.0%	15.6%	9.7%	12.5%	5.0%
		C	3.3%	33.0%	26.7%	15.1%	15.2%	6.6%
		I	3.3%	33.0%	26.7%	15.1%	15.2%	6.6%
C								
	60-72							
		HA	3.5%	24.2%	47.3%	15.8%	3.1%	6.2%
		H	1.8%	15.3%	53.4%	19.2%	4.5%	5.8%
		C	0.3%	5.7%	52.2%	31.0%	5.1%	5.8%
		I	4.9%	10.8%	37.7%	33.8%	6.0%	6.9%
	73-85							
		HA	2.4%	17.6%	47.5%	16.8%	5.8%	9.9%
		H	1.2%	10.7%	51.4%	19.6%	8.0%	9.0%
		C	0.2%	3.9%	48.3%	30.3%	8.7%	8.6%
		I	3.2%	7.3%	35.2%	33.4%	10.5%	10.4%
	>85							
		HA	1.2%	14.4%	40.2%	17.1%	7.8%	19.3%
		H	0.6%	8.7%	43.0%	19.8%	10.7%	17.3%
		C	0.1%	3.0%	39.4%	29.8%	11.4%	16.2%
		I	1.5%	5.7%	28.2%	32.2%	13.4%	19.1%
D								
	60-72							
		HA	1.9%	7.6%	20.8%	51.2%	9.9%	8.6%
		H	0.4%	2.0%	14.9%	59.1%	16.9%	6.8%
		C	0.1%	0.8%	11.3%	62.5%	18.0%	7.3%
		I	3.6%	4.6%	11.8%	47.0%	23.0%	10.0%
	73-85							
		HA	0.8%	6.0%	15.5%	47.8%	12.9%	16.9%
		H	0.2%	1.5%	10.8%	53.3%	21.3%	13.0%
		C	0.1%	0.6%	8.0%	55.3%	22.4%	13.6%
		I	1.4%	3.4%	8.2%	40.7%	27.9%	18.3%
	>85							
		HA	0.6%	2.9%	14.7%	42.1%	14.4%	25.3%

		H	0.1%	0.7%	10.1%	46.5%	23.5%	19.2%
		C	0.0%	0.3%	7.4%	47.8%	24.4%	20.0%
		I	1.1%	1.6%	7.4%	34.2%	29.6%	26.1%
E								
	60-72							
		HA	1.4%	7.8%	7.3%	20.9%	46.0%	16.6%
		H	0.2%	1.3%	2.2%	16.7%	64.5%	15.2%
		C	0.0%	0.1%	0.6%	14.1%	74.5%	10.7%
		I	0.1%	0.8%	0.8%	10.5%	66.7%	21.2%
	73-85							
		HA	0.4%	2.3%	4.9%	15.3%	55.3%	21.8%
		H	0.1%	0.3%	1.3%	11.0%	69.5%	17.9%
		C	0.0%	0.1%	0.9%	12.6%	63.7%	22.7%
		I	0.2%	1.0%	2.1%	4.4%	62.4%	29.9%
	>85							
		HA	0.3%	1.7%	3.8%	12.0%	46.1%	36.1%
		H	0.0%	0.3%	1.0%	8.9%	59.4%	30.4%
		C	0.0%	0.1%	0.7%	9.7%	52.4%	37.2%
		I	0.1%	0.5%	1.2%	3.4%	57.8%	37.1%

5.3. Transition Matrix for Living Arrangement

As living arrangement is one of the predictors that explain the variations of ending statuses among individuals, this research develops another prediction model to forecast the individual's future living arrangement. The results are shown in Table 5-10.

While examining the data, as mentioned previously, sample data is frequently sparse. Female and male living arrangement transition matrixes are displayed from Table 5-11 to Table 5-16. The probabilities estimated by neighbor group are marked.

The living arrangement is highly correlated to individuals' independence; it is also correlated to their capitation rate level and age. For example, ages 60-72 female individuals with starting LTCS=A living in nursing homes are more likely to move to community assisted living or home than to stay in a nursing home. This result probably occurs because the individuals in the lowest capitation rate group are more capable of recovering as they are considered relatively healthy, and the reasons they stayed in nursing homes may be temporary medical conditions.

The probability of females staying at home with a helper is smaller than males, and females are more likely to be admitted to community assisted living or nursing homes. One of the valid reasons is that female life expectancy is longer than male, so males are more likely to have spouses. Therefore, females are more likely to receive assistance from community assisted living or nursing homes. It is also unlikely that individuals with starting LTCS=E (highest cost group) live at home without helpers across all age groups and both genders.

Table 5-10: Multinomial Regression of Transitions for Living Arrangement

	Ending Living Arrangement			
Starting Living Arrangement				
Home Alone (HA)				
	HA	H	C	I
Intercept	-	0.02	0.01	0.00
LTCS=B	-	1.80	2.38	2.04
LTCS=C	-	2.17	4.47	2.84
LTCS=D	-	3.66	10.34	11.64
LTCS=D	-	4.99	16.82	92.45
Recovery	-	1.18	0.85	0.18
Impairment	-	2.59	11.62	61.23
Age: 73-85	-	1.05	1.55	1.54
Age:>85	-	0.61	2.90	2.37
Home with helpers (H)				
	HA	H	C	I
Intercept	0.09	-	0.01	0.00

LTCS=B	0.71	-	2.14	1.73
LTCS=C	0.38	-	3.07	2.17
LTCS=D	0.25	-	4.07	4.31
LTCS=D	0.10	-	4.84	38.19
Recovery	2.29	-	1.67	0.19
Impairment	1.11	-	4.24	27.90
Age: 73-85	1.11	-	1.29	1.45
Age:>85	0.79	-	1.85	1.96
Female	1.13	-	0.69	0.68
Community Assisted living (C)				
	HA	H	C	I
Intercept	0.11	0.10	-	0.00
LTCS=B	0.23	0.23	-	1.09
LTCS=C	0.03	0.20	-	1.24
LTCS=D	0.03	0.12	-	2.91
LTCS=D	0.00	0.11	-	20.60
Recovery	16.37	2.60	-	0.24
Impairment	1.01	2.01	-	19.24
Age: 73-85	0.67	0.37	-	2.89
Age:>85	0.13	0.09	-	3.30
Nursing Home (I)				
	HA	H	C	I
Intercept	6.77	0.91	5.06	-
LTCS=C	0.08	0.47	0.46	-
LTCS=D	0.01	0.11	0.09	-
LTCS=D	0.00	0.03	0.02	-
Recovery	81.19	13.83	12.48	-
Impairment	0.14	0.32	0.46	-
Age: 73-85	0.43	0.84	0.99	-
Age:>85	0.65	0.38	0.66	-

The model can improve the ability to project future LTCS populations since individuals' living arrangements may change over time. In addition to long term care planning at the individual level, these transition matrixes are also beneficial for more general health care facilities planning.

Table 5-11: Living Arrangement Transition Matrix--Female 60-72

Starting LTCS	Ending LTCS	Living Arrangement	HA	H	C	I
A	A	HA	97.4%	1.9%	0.6%	0.1%
A	A	H	9.1%	90.2%	0.6%	0.1%
A	A	C	9.0%	8.3%	82.5%	0.2%
A	A	I	49.3%	6.6%	36.8%	7.3%
A	B	HA	82.6%	4.2%	5.8%	7.4%
A	B	H	9.4%	84.6%	2.5%	3.4%
A	B	C	8.1%	14.9%	73.5%	3.5%
A	B	I	20.3%	6.5%	51.2%	22.1%
A	C	HA	82.6%	4.2%	5.8%	7.4%
A	C	H	9.4%	84.6%	2.5%	3.4%
A	C	C	8.1%	14.9%	73.5%	3.5%
A	C	I	20.3%	6.5%	51.2%	22.1%
A	D	HA	82.6%	4.2%	5.8%	7.4%
A	D	H	9.4%	84.6%	2.5%	3.4%
A	D	C	8.1%	14.9%	73.5%	3.5%
A	D	I	20.3%	6.5%	51.2%	22.1%
A	E	HA	82.6%	4.2%	5.8%	7.4%
A	E	H	9.4%	84.6%	2.5%	3.4%
A	E	C	8.1%	14.9%	73.5%	3.5%
A	E	I	20.3%	6.5%	51.2%	22.1%
B	A	HA	94.8%	4.0%	1.2%	0.1%
B	A	H	13.8%	84.0%	2.1%	0.0%
B	A	C	27.7%	4.1%	68.2%	0.0%
B	A	I	27.7%	4.1%	68.2%	0.0%
B	B	HA	95.0%	3.4%	1.4%	0.3%
B	B	H	6.6%	91.8%	1.4%	0.2%
B	B	C	2.4%	2.2%	95.2%	0.3%
B	B	I	49.3%	6.6%	36.8%	7.3%
B	C	HA	69.4%	6.3%	11.6%	12.6%
B	C	H	6.6%	82.4%	5.3%	5.8%
B	C	C	2.2%	4.1%	89.0%	4.7%
B	C	I	20.3%	6.5%	51.2%	22.1%
B	D	HA	69.4%	6.3%	11.6%	12.6%
B	D	H	6.6%	82.4%	5.3%	5.8%
B	D	C	2.2%	4.1%	89.0%	4.7%
B	D	I	20.3%	6.5%	51.2%	22.1%
B	E	HA	69.4%	6.3%	11.6%	12.6%
B	E	H	6.6%	82.4%	5.3%	5.8%
B	E	C	2.2%	4.1%	89.0%	4.7%
B	E	I	20.3%	6.5%	51.2%	22.1%

C	A	HA	93.1%	4.7%	2.1%	0.1%
C	A	H	7.9%	88.9%	3.2%	0.1%
C	A	C	5.5%	4.7%	89.7%	0.1%
C	A	I	56.1%	7.3%	35.4%	1.2%
C	B	HA	93.1%	4.7%	2.1%	0.1%
C	B	H	7.9%	88.9%	3.2%	0.1%
C	B	C	5.5%	4.7%	89.7%	0.1%
C	B	I	56.1%	7.3%	35.4%	1.2%
C	C	HA	93.2%	4.0%	2.5%	0.4%
C	C	H	3.6%	94.0%	2.0%	0.3%
C	C	C	0.4%	2.0%	97.4%	0.3%
C	C	I	13.1%	10.0%	53.6%	23.2%
C	D	HA	59.6%	6.5%	18.7%	15.1%
C	D	H	3.5%	81.8%	7.5%	7.2%
C	D	C	0.3%	3.7%	90.6%	5.4%
C	D	I	3.4%	6.1%	46.6%	44.0%
C	E	HA	59.6%	6.5%	18.7%	15.1%
C	E	H	3.5%	81.8%	7.5%	7.2%
C	E	C	0.3%	3.7%	90.6%	5.4%
C	E	I	3.4%	6.1%	46.6%	44.0%
D	A	HA	87.7%	7.4%	4.7%	0.3%
D	A	H	5.2%	90.3%	4.3%	0.1%
D	A	C	4.2%	2.8%	92.8%	0.2%
D	A	I	27.7%	12.0%	51.4%	8.9%
D	B	HA	87.7%	7.4%	4.7%	0.3%
D	B	H	5.2%	90.3%	4.3%	0.1%
D	B	C	4.2%	2.8%	92.8%	0.2%
D	B	I	27.7%	12.0%	51.4%	8.9%
D	C	HA	87.7%	7.4%	4.7%	0.3%
D	C	H	5.2%	90.3%	4.3%	0.1%
D	C	C	4.2%	2.8%	92.8%	0.2%
D	C	I	27.7%	12.0%	51.4%	8.9%
D	D	HA	86.9%	6.2%	5.4%	1.5%
D	D	H	2.4%	94.3%	2.7%	0.6%
D	D	C	0.3%	1.2%	97.9%	0.7%
D	D	I	2.4%	6.1%	29.0%	62.5%
D	E	HA	33.9%	6.3%	24.7%	35.2%
D	E	H	2.1%	75.5%	9.2%	13.2%
D	E	C	0.2%	2.0%	85.8%	11.9%
D	E	I	0.4%	2.5%	17.0%	80.0%
E	A	HA	81.6%	9.4%	7.1%	2.0%

E	A	H	2.2%	91.6%	5.2%	1.0%
E	A	C	0.5%	2.8%	95.5%	1.2%
E	A	I	15.4%	13.1%	35.2%	36.3%
E	B	HA	81.6%	9.4%	7.1%	2.0%
E	B	H	2.2%	91.6%	5.2%	1.0%
E	B	C	0.5%	2.8%	95.5%	1.2%
E	B	I	15.4%	13.1%	35.2%	36.3%
E	C	HA	81.6%	9.4%	7.1%	2.0%
E	C	H	2.2%	91.6%	5.2%	1.0%
E	C	C	0.5%	2.8%	95.5%	1.2%
E	C	I	15.4%	13.1%	35.2%	36.3%
E	D	HA	81.6%	9.4%	7.1%	2.0%
E	D	H	2.2%	91.6%	5.2%	1.0%
E	D	C	0.5%	2.8%	95.5%	1.2%
E	D	I	15.4%	13.1%	35.2%	36.3%
E	E	HA	75.0%	7.3%	7.6%	10.1%
E	E	H	1.0%	90.9%	3.1%	5.0%
E	E	C	0.0%	1.1%	94.1%	4.8%
E	E	I	0.5%	2.4%	7.0%	90.2%

Table 5-12:Living Arrangement Transition Matrix--Female 73-85

Starting LTCS	Ending LTCS	Living Arrangement	HA	H	C	I
A	A	HA	96.9%	2.0%	0.9%	0.2%
A	A	H	9.9%	89.1%	0.8%	0.2%
A	A	C	6.6%	3.3%	89.5%	0.6%
A	A	I	6.6%	3.3%	89.5%	0.6%
A	B	HA	77.0%	4.1%	8.4%	10.6%
A	B	H	10.1%	81.9%	3.2%	4.8%
A	B	C	5.8%	5.8%	77.7%	10.7%
A	B	I	10.0%	6.3%	58.4%	25.4%
A	C	HA	77.0%	4.1%	8.4%	10.6%
A	C	H	10.1%	81.9%	3.2%	4.8%
A	C	C	5.8%	5.8%	77.7%	10.7%
A	C	I	10.0%	6.3%	58.4%	25.4%
A	D	HA	77.0%	4.1%	8.4%	10.6%
A	D	H	10.1%	81.9%	3.2%	4.8%
A	D	C	5.8%	5.8%	77.7%	10.7%
A	D	I	10.0%	6.3%	58.4%	25.4%
A	E	HA	77.0%	4.1%	8.4%	10.6%

A	E	H	10.1%	81.9%	3.2%	4.8%
A	E	C	5.8%	5.8%	77.7%	10.7%
A	E	I	10.0%	6.3%	58.4%	25.4%
B	A	HA	94.0%	4.1%	1.8%	0.1%
B	A	H	15.0%	82.3%	2.7%	0.1%
B	A	C	21.1%	1.7%	77.1%	0.2%
B	A	I	76.1%	3.4%	20.2%	0.3%
B	B	HA	7.2%	90.7%	1.8%	0.3%
B	B	H	1.6%	0.8%	96.8%	0.8%
B	B	C	30.0%	7.9%	51.8%	10.3%
B	B	I	91.5%	4.1%	3.8%	0.6%
B	C	HA	61.2%	5.9%	15.8%	17.2%
B	C	H	6.9%	78.6%	6.5%	7.9%
B	C	C	1.4%	1.4%	84.4%	12.8%
B	C	I	10.0%	6.3%	58.4%	25.4%
B	D	HA	61.2%	5.9%	15.8%	17.2%
B	D	H	6.9%	78.6%	6.5%	7.9%
B	D	C	1.4%	1.4%	84.4%	12.8%
B	D	I	10.0%	6.3%	58.4%	25.4%
B	E	HA	61.2%	5.9%	15.8%	17.2%
B	E	H	6.9%	78.6%	6.5%	7.9%
B	E	C	1.4%	1.4%	84.4%	12.8%
B	E	I	10.0%	6.3%	58.4%	25.4%
C	A	HA	91.8%	4.8%	3.3%	0.1%
C	A	H	8.5%	87.3%	4.1%	0.1%
C	A	C	3.9%	1.8%	94.1%	0.2%
C	A	I	36.2%	9.2%	52.7%	1.9%
C	B	HA	91.8%	4.8%	3.3%	0.1%
C	B	H	8.5%	87.3%	4.1%	0.1%
C	B	C	3.9%	1.8%	94.1%	0.2%
C	B	I	36.2%	9.2%	52.7%	1.9%
C	C	HA	91.5%	4.1%	3.8%	0.6%
C	C	H	4.0%	93.0%	2.6%	0.4%
C	C	C	0.3%	0.7%	98.2%	0.9%
C	C	I	6.2%	9.3%	58.8%	25.7%
C	D	HA	50.2%	5.8%	24.4%	19.6%
C	D	H	3.7%	77.3%	9.2%	9.8%
C	D	C	0.2%	1.3%	84.1%	14.4%
C	D	I	1.5%	5.3%	47.7%	45.5%
C	E	HA	50.2%	5.8%	24.4%	19.6%
C	E	H	3.7%	77.3%	9.2%	9.8%

C	E	C	0.2%	1.3%	84.1%	14.4%
C	E	I	1.5%	5.3%	47.7%	45.5%
D	A	HA	85.1%	7.5%	7.0%	0.4%
D	A	H	5.7%	88.7%	5.5%	0.2%
D	A	C	2.9%	1.1%	95.6%	0.5%
D	A	I	14.5%	12.3%	62.3%	10.9%
D	B	HA	85.1%	7.5%	7.0%	0.4%
D	B	H	5.7%	88.7%	5.5%	0.2%
D	B	C	2.9%	1.1%	95.6%	0.5%
D	B	I	14.5%	12.3%	62.3%	10.9%
D	C	HA	85.1%	7.5%	7.0%	0.4%
D	C	H	5.7%	88.7%	5.5%	0.2%
D	C	C	2.9%	1.1%	95.6%	0.5%
D	C	I	14.5%	12.3%	62.3%	10.9%
D	D	HA	83.5%	6.3%	8.1%	2.2%
D	D	H	2.6%	93.1%	3.5%	0.8%
D	D	C	0.2%	0.4%	97.4%	2.0%
D	D	I	1.1%	5.3%	29.5%	64.2%
D	E	HA	25.5%	5.0%	28.7%	40.9%
D	E	H	2.2%	69.4%	11.0%	17.5%
D	E	C	0.1%	0.6%	70.8%	28.4%
D	E	I	0.2%	2.1%	17.0%	80.7%
E	A	HA	77.4%	9.3%	10.4%	2.9%
E	A	H	2.4%	89.6%	6.6%	1.4%
E	A	C	0.4%	1.0%	95.2%	3.4%
E	A	I	7.4%	12.4%	39.3%	40.9%
E	B	HA	77.4%	9.3%	10.4%	2.9%
E	B	H	2.4%	89.6%	6.6%	1.4%
E	B	C	0.4%	1.0%	95.2%	3.4%
E	B	I	7.4%	12.4%	39.3%	40.9%
E	C	HA	77.4%	9.3%	10.4%	2.9%
E	C	H	2.4%	89.6%	6.6%	1.4%
E	C	C	0.4%	1.0%	95.2%	3.4%
E	C	I	7.4%	12.4%	39.3%	40.9%
E	D	HA	77.4%	9.3%	10.4%	2.9%
E	D	H	2.4%	89.6%	6.6%	1.4%
E	D	C	0.4%	1.0%	95.2%	3.4%
E	D	I	7.4%	12.4%	39.3%	40.9%
E	E	HA	68.2%	7.0%	10.7%	14.2%
E	E	H	1.0%	88.0%	3.9%	7.1%
E	E	C	0.0%	0.4%	86.8%	12.8%

E	E	I	0.2%	2.0%	7.0%	90.8%

Table 5-13:Living Arrangement Transition Matrix--Female >85

Starting LTCS	Ending LTCS	Living Arrangement	HA	H	C	I
A	A	HA	96.8%	1.2%	1.7%	0.3%
A	A	H	7.3%	91.3%	1.2%	0.3%
A	A	C	1.3%	0.9%	97.0%	0.8%
A	A	I	48.4%	3.8%	36.9%	11.0%
A	B	HA	69.2%	2.2%	14.1%	14.6%
A	B	H	7.2%	81.8%	4.5%	6.5%
A	B	C	1.2%	1.5%	84.1%	13.3%
A	B	I	1.2%	1.5%	84.1%	13.3%
A	C	HA	69.2%	2.2%	14.1%	14.6%
A	C	H	7.2%	81.8%	4.5%	6.5%
A	C	C	1.2%	1.5%	84.1%	13.3%
A	C	I	1.2%	1.5%	84.1%	13.3%
A	D	HA	69.2%	2.2%	14.1%	14.6%
A	D	H	7.2%	81.8%	4.5%	6.5%
A	D	C	1.2%	1.5%	84.1%	13.3%
A	D	I	1.2%	1.5%	84.1%	13.3%
A	E	HA	69.2%	2.2%	14.1%	14.6%
A	E	H	7.2%	81.8%	4.5%	6.5%
A	E	C	1.2%	1.5%	84.1%	13.3%
A	E	I	1.2%	1.5%	84.1%	13.3%
B	A	HA	94.1%	2.4%	3.3%	0.1%
B	A	H	11.0%	84.9%	4.0%	0.1%
B	A	C	4.8%	0.5%	94.5%	0.2%
B	A	I	88.2%	1.2%	10.3%	0.3%
B	B	HA	93.4%	2.0%	3.9%	0.7%
B	B	H	5.2%	91.8%	2.6%	0.5%
B	B	C	0.3%	0.2%	98.6%	0.9%
B	B	I	48.4%	3.8%	36.9%	11.0%
B	C	HA	50.7%	2.8%	24.6%	21.9%
B	C	H	4.8%	75.8%	9.0%	10.4%
B	C	C	0.3%	0.3%	84.8%	14.6%
B	C	I	18.4%	3.5%	47.4%	30.7%
B	D	HA	50.7%	2.8%	24.6%	21.9%
B	D	H	4.8%	75.8%	9.0%	10.4%
B	D	C	0.3%	0.3%	84.8%	14.6%

B	D	I	18.4%	3.5%	47.4%	30.7%
B	E	HA	50.7%	2.8%	24.6%	21.9%
B	E	H	4.8%	75.8%	9.0%	10.4%
B	E	C	0.3%	0.3%	84.8%	14.6%
B	E	I	18.4%	3.5%	47.4%	30.7%
C	A	HA	91.0%	2.8%	6.1%	0.2%
C	A	H	6.2%	87.9%	5.9%	0.1%
C	A	C	0.8%	0.5%	98.6%	0.2%
C	A	I	57.1%	4.4%	36.7%	1.9%
C	B	HA	91.0%	2.8%	6.1%	0.2%
C	B	H	6.2%	87.9%	5.9%	0.1%
C	B	C	0.8%	0.5%	98.6%	0.2%
C	B	I	57.1%	4.4%	36.7%	1.9%
C	C	HA	89.8%	2.3%	7.0%	0.9%
C	C	H	2.8%	92.9%	3.7%	0.6%
C	C	C	0.1%	0.2%	98.8%	1.0%
C	C	I	12.0%	5.4%	50.0%	32.6%
C	D	HA	38.8%	2.6%	35.3%	23.3%
C	D	H	2.5%	72.7%	12.4%	12.5%
C	D	C	0.0%	0.3%	83.3%	16.3%
C	D	I	2.8%	3.0%	39.0%	55.3%
C	E	HA	38.8%	2.6%	35.3%	23.3%
C	E	H	2.5%	72.7%	12.4%	12.5%
C	E	C	0.0%	0.3%	83.3%	16.3%
C	E	I	2.8%	3.0%	39.0%	55.3%
D	A	HA	82.4%	4.3%	12.7%	0.6%
D	A	H	4.0%	88.0%	7.8%	0.2%
D	A	C	0.6%	0.3%	98.6%	0.6%
D	A	I	27.5%	7.0%	52.1%	13.5%
D	B	HA	82.4%	4.3%	12.7%	0.6%
D	B	H	4.0%	88.0%	7.8%	0.2%
D	B	C	0.6%	0.3%	98.6%	0.6%
D	B	I	27.5%	7.0%	52.1%	13.5%
D	C	HA	82.4%	4.3%	12.7%	0.6%
D	C	H	4.0%	88.0%	7.8%	0.2%
D	C	C	0.6%	0.3%	98.6%	0.6%
D	C	I	27.5%	7.0%	52.1%	13.5%
D	D	HA	79.0%	3.5%	14.3%	3.2%
D	D	H	1.8%	92.1%	4.9%	1.1%
D	D	C	0.0%	0.1%	97.5%	2.3%
D	D	I	1.8%	2.7%	22.5%	73.0%

D	E	HA	17.6%	2.0%	37.1%	43.3%
D	E	H	1.4%	62.9%	14.2%	21.5%
D	E	C	0.0%	0.1%	68.5%	31.4%
D	E	I	0.3%	1.0%	12.2%	86.4%
E	A	HA	72.5%	5.1%	18.2%	4.1%
E	A	H	1.7%	87.3%	9.2%	1.8%
E	A	C	0.1%	0.2%	95.8%	3.9%
E	A	I	13.4%	6.7%	31.3%	48.6%
E	B	HA	72.5%	5.1%	18.2%	4.1%
E	B	H	1.7%	87.3%	9.2%	1.8%
E	B	C	0.1%	0.2%	95.8%	3.9%
E	B	I	13.4%	6.7%	31.3%	48.6%
E	C	HA	72.5%	5.1%	18.2%	4.1%
E	C	H	1.7%	87.3%	9.2%	1.8%
E	C	C	0.1%	0.2%	95.8%	3.9%
E	C	I	13.4%	6.7%	31.3%	48.6%
E	D	HA	72.5%	5.1%	18.2%	4.1%
E	D	H	1.7%	87.3%	9.2%	1.8%
E	D	C	0.1%	0.2%	95.8%	3.9%
E	D	I	13.4%	6.7%	31.3%	48.6%
E	E	HA	59.8%	3.6%	17.6%	19.1%
E	E	H	0.7%	84.8%	5.4%	9.2%
E	E	C	0.0%	0.1%	85.5%	14.4%

Table 5-14:Living Arrangement Transition Matrix--Male 60-72

Starting LTCS	Ending LTCS	Living Arrangement	HA	H	C	I
A	A	HA	97.4%	1.9%	0.6%	0.1%
A	A	H	8.1%	90.8%	0.9%	0.2%
A	A	C	9.0%	8.3%	82.5%	0.2%
A	A	I	49.3%	6.6%	36.8%	7.3%
A	B	HA	82.6%	4.2%	5.8%	7.4%
A	B	H	8.2%	83.2%	3.6%	4.9%
A	B	C	8.1%	14.9%	73.5%	3.5%
A	B	I	20.3%	6.5%	51.2%	22.1%
A	C	HA	82.6%	4.2%	5.8%	7.4%
A	C	H	8.2%	83.2%	3.6%	4.9%
A	C	C	8.1%	14.9%	73.5%	3.5%
A	C	I	20.3%	6.5%	51.2%	22.1%
A	D	HA	82.6%	4.2%	5.8%	7.4%
A	D	H	8.2%	83.2%	3.6%	4.9%

A	D	C	8.1%	14.9%	73.5%	3.5%
A	D	I	20.3%	6.5%	51.2%	22.1%
A	E	HA	82.6%	4.2%	5.8%	7.4%
A	E	H	8.2%	83.2%	3.6%	4.9%
A	E	C	8.1%	14.9%	73.5%	3.5%
A	E	I	20.3%	6.5%	51.2%	22.1%
B	A	HA	94.8%	4.0%	1.2%	0.1%
B	A	H	12.3%	84.5%	3.1%	0.1%
B	A	C	27.7%	4.1%	68.2%	0.0%
B	A	I	87.7%	2.0%	10.1%	0.2%
B	B	HA	95.0%	3.4%	1.4%	0.3%
B	B	H	5.8%	91.8%	2.0%	0.3%
B	B	C	2.4%	2.2%	95.2%	0.3%
B	B	I	49.3%	6.6%	36.8%	7.3%
B	C	HA	69.4%	6.3%	11.6%	12.6%
B	C	H	5.6%	79.0%	7.4%	8.1%
B	C	C	2.2%	4.1%	89.0%	4.7%
B	C	I	20.3%	6.5%	51.2%	22.1%
B	D	HA	69.4%	6.3%	11.6%	12.6%
B	D	H	5.6%	79.0%	7.4%	8.1%
B	D	C	2.2%	4.1%	89.0%	4.7%
B	D	I	20.3%	6.5%	51.2%	22.1%
B	E	HA	69.4%	6.3%	11.6%	12.6%
B	E	H	5.6%	79.0%	7.4%	8.1%
B	E	C	2.2%	4.1%	89.0%	4.7%
B	E	I	20.3%	6.5%	51.2%	22.1%
C	A	HA	93.1%	4.7%	2.1%	0.1%
C	A	H	6.9%	88.3%	4.7%	0.1%
C	A	C	5.5%	4.7%	89.7%	0.1%
C	A	I	56.1%	7.3%	35.4%	1.2%
C	B	HA	93.1%	4.7%	2.1%	0.1%
C	B	H	6.9%	88.3%	4.7%	0.1%
C	B	C	5.5%	4.7%	89.7%	0.1%
C	B	I	56.1%	7.3%	35.4%	1.2%
C	C	HA	93.2%	4.0%	2.5%	0.4%
C	C	H	3.2%	93.4%	3.0%	0.4%
C	C	C	0.4%	2.0%	97.4%	0.3%
C	C	I	13.1%	10.0%	53.6%	23.2%
C	D	HA	59.6%	6.5%	18.7%	15.1%
C	D	H	2.9%	76.9%	10.3%	9.9%
C	D	C	0.3%	3.7%	90.6%	5.4%

C	D	I	3.4%	6.1%	46.6%	44.0%
C	E	HA	59.6%	6.5%	18.7%	15.1%
C	E	H	2.9%	76.9%	10.3%	9.9%
C	E	C	0.3%	3.7%	90.6%	5.4%
C	E	I	3.4%	6.1%	46.6%	44.0%
D	A	HA	87.7%	7.4%	4.7%	0.3%
D	A	H	4.6%	89.1%	6.2%	0.2%
D	A	C	4.2%	2.8%	92.8%	0.2%
D	A	I	27.7%	12.0%	51.4%	8.9%
D	B	HA	87.7%	7.4%	4.7%	0.3%
D	B	H	4.6%	89.1%	6.2%	0.2%
D	B	C	4.2%	2.8%	92.8%	0.2%
D	B	I	27.7%	12.0%	51.4%	8.9%
D	C	HA	87.7%	7.4%	4.7%	0.3%
D	C	H	4.6%	89.1%	6.2%	0.2%
D	C	C	4.2%	2.8%	92.8%	0.2%
D	C	I	27.7%	12.0%	51.4%	8.9%
D	D	HA	86.9%	6.2%	5.4%	1.5%
D	D	H	2.1%	93.2%	3.9%	0.9%
D	D	C	0.3%	1.2%	97.9%	0.7%
D	D	I	2.4%	6.1%	29.0%	62.5%
D	E	HA	33.9%	6.3%	24.7%	35.2%
D	E	H	1.7%	68.6%	12.2%	17.5%
D	E	C	0.2%	2.0%	85.8%	11.9%
D	E	I	0.4%	2.5%	17.0%	80.0%
E	A	HA	81.6%	9.4%	7.1%	2.0%
E	A	H	1.9%	89.3%	7.4%	1.4%
E	A	C	0.5%	2.8%	95.5%	1.2%
E	A	I	15.4%	13.1%	35.2%	36.3%
E	B	HA	81.6%	9.4%	7.1%	2.0%
E	B	H	1.9%	89.3%	7.4%	1.4%
E	B	C	0.5%	2.8%	95.5%	1.2%
E	B	I	15.4%	13.1%	35.2%	36.3%
E	C	HA	81.6%	9.4%	7.1%	2.0%
E	C	H	1.9%	89.3%	7.4%	1.4%
E	C	C	0.5%	2.8%	95.5%	1.2%
E	C	I	15.4%	13.1%	35.2%	36.3%
E	D	HA	81.6%	9.4%	7.1%	2.0%
E	D	H	1.9%	89.3%	7.4%	1.4%
E	D	C	0.5%	2.8%	95.5%	1.2%
E	D	I	15.4%	13.1%	35.2%	36.3%

E	E	HA	75.0%	7.3%	7.6%	10.1%
E	E	H	0.8%	87.7%	4.4%	7.1%
E	E	C	0.0%	1.1%	94.1%	4.8%
E	E	I	0.5%	2.4%	7.0%	90.2%

Table 5-15:Living Arrangement Transition Matrix--Male 73-85

Starting LTCS	Ending LTCS	Living Arrangement	HA	H	C	I
A	A	HA	96.9%	2.0%	0.9%	0.2%
A	A	H	8.9%	89.7%	1.2%	0.3%
A	A	C	6.6%	3.3%	89.5%	0.6%
A	A	I	30.0%	7.9%	51.8%	10.3%
A	B	HA	77.0%	4.1%	8.4%	10.6%
A	B	H	8.8%	79.9%	4.5%	6.9%
A	B	C	5.8%	5.8%	77.7%	10.7%
A	B	I	10.0%	6.3%	58.4%	25.4%
A	C	HA	77.0%	4.1%	8.4%	10.6%
A	C	H	8.8%	79.9%	4.5%	6.9%
A	C	C	5.8%	5.8%	77.7%	10.7%
A	C	I	10.0%	6.3%	58.4%	25.4%
A	D	HA	77.0%	4.1%	8.4%	10.6%
A	D	H	8.8%	79.9%	4.5%	6.9%
A	D	C	5.8%	5.8%	77.7%	10.7%
A	D	I	10.0%	6.3%	58.4%	25.4%
A	E	HA	77.0%	4.1%	8.4%	10.6%
A	E	H	8.8%	79.9%	4.5%	6.9%
A	E	C	5.8%	5.8%	77.7%	10.7%
A	E	I	10.0%	6.3%	58.4%	25.4%
B	A	HA	94.0%	4.1%	1.8%	0.1%
B	A	H	13.3%	82.6%	3.9%	0.1%
B	A	C	21.1%	1.7%	77.1%	0.2%
B	A	I	21.1%	1.7%	77.1%	0.2%
B	B	HA	94.0%	3.5%	2.1%	0.4%
B	B	H	6.4%	90.6%	2.6%	0.5%
B	B	C	1.6%	0.8%	96.8%	0.8%
B	B	I	30.0%	7.9%	51.8%	10.3%
B	C	HA	61.2%	5.9%	15.8%	17.2%
B	C	H	5.8%	74.2%	9.0%	11.0%
B	C	C	1.4%	1.4%	84.4%	12.8%

B	C	I	10.0%	6.3%	58.4%	25.4%
B	D	HA	61.2%	5.9%	15.8%	17.2%
B	D	H	5.8%	74.2%	9.0%	11.0%
B	D	C	1.4%	1.4%	84.4%	12.8%
B	D	I	10.0%	6.3%	58.4%	25.4%
B	E	HA	61.2%	5.9%	15.8%	17.2%
B	E	H	5.8%	74.2%	9.0%	11.0%
B	E	C	1.4%	1.4%	84.4%	12.8%
B	E	I	10.0%	6.3%	58.4%	25.4%
C	A	HA	91.8%	4.8%	3.3%	0.1%
C	A	H	7.5%	86.5%	5.9%	0.1%
C	A	C	3.9%	1.8%	94.1%	0.2%
C	A	I	3.9%	1.8%	94.1%	0.2%
C	B	HA	91.8%	4.8%	3.3%	0.1%
C	B	H	7.5%	86.5%	5.9%	0.1%
C	B	C	3.9%	1.8%	94.1%	0.2%
C	B	I	3.9%	1.8%	94.1%	0.2%
C	C	HA	91.5%	4.1%	3.8%	0.6%
C	C	H	3.5%	92.1%	3.8%	0.6%
C	C	C	0.3%	0.7%	98.2%	0.9%
C	C	I	6.2%	9.3%	58.8%	25.7%
C	D	HA	50.2%	5.8%	24.4%	19.6%
C	D	H	3.0%	71.4%	12.4%	13.3%
C	D	C	0.2%	1.3%	84.1%	14.4%
C	D	I	1.5%	5.3%	47.7%	45.5%
C	E	HA	50.2%	5.8%	24.4%	19.6%
C	E	H	3.0%	71.4%	12.4%	13.3%
C	E	C	0.2%	1.3%	84.1%	14.4%
C	E	I	1.5%	5.3%	47.7%	45.5%
D	A	HA	85.1%	7.5%	7.0%	0.4%
D	A	H	4.9%	87.0%	7.9%	0.2%
D	A	C	2.9%	1.1%	95.6%	0.5%
D	A	I	14.5%	12.3%	62.3%	10.9%
D	B	HA	85.1%	7.5%	7.0%	0.4%
D	B	H	4.9%	87.0%	7.9%	0.2%
D	B	C	2.9%	1.1%	95.6%	0.5%
D	B	I	14.5%	12.3%	62.3%	10.9%
D	C	HA	85.1%	7.5%	7.0%	0.4%
D	C	H	4.9%	87.0%	7.9%	0.2%
D	C	C	2.9%	1.1%	95.6%	0.5%
D	C	I	14.5%	12.3%	62.3%	10.9%

D	D	HA	83.5%	6.3%	8.1%	2.2%
D	D	H	2.3%	91.6%	5.0%	1.2%
D	D	C	0.2%	0.4%	97.4%	2.0%
D	D	I	1.1%	5.3%	29.5%	64.2%
D	E	HA	25.5%	5.0%	28.7%	40.9%
D	E	H	1.7%	61.5%	14.1%	22.7%
D	E	C	0.1%	0.6%	70.8%	28.4%
D	E	I	0.2%	2.1%	17.0%	80.7%
E	A	HA	77.4%	9.3%	10.4%	2.9%
E	A	H	2.1%	86.7%	9.3%	2.0%
E	A	C	0.4%	1.0%	95.2%	3.4%
E	A	I	7.4%	12.4%	39.3%	40.9%
E	B	HA	77.4%	9.3%	10.4%	2.9%
E	B	H	2.1%	86.7%	9.3%	2.0%
E	B	C	0.4%	1.0%	95.2%	3.4%
E	B	I	7.4%	12.4%	39.3%	40.9%
E	C	HA	77.4%	9.3%	10.4%	2.9%
E	C	H	2.1%	86.7%	9.3%	2.0%
E	C	C	0.4%	1.0%	95.2%	3.4%
E	C	I	7.4%	12.4%	39.3%	40.9%
E	D	HA	77.4%	9.3%	10.4%	2.9%
E	D	H	2.1%	86.7%	9.3%	2.0%
E	D	C	0.4%	1.0%	95.2%	3.4%
E	D	I	7.4%	12.4%	39.3%	40.9%
E	E	HA	68.2%	7.0%	10.7%	14.2%
E	E	H	0.9%	83.9%	5.4%	9.8%
E	E	C	0.0%	0.4%	86.8%	12.8%
E	E	I	0.2%	2.0%	7.0%	90.8%

Table 5-16:Table 36:Living Arrangement Transition Matrix--Male >85

Starting LTCS	Ending LTCS	Living Arrangement	HA	H	C	I
A	A	HA	96.8%	1.2%	1.7%	0.3%
A	A	H	6.5%	91.4%	1.7%	0.4%
A	A	C	1.3%	0.9%	97.0%	0.8%
A	A	I	1.3%	0.9%	97.0%	0.8%
A	B	HA	69.2%	2.2%	14.1%	14.6%
A	B	H	6.1%	78.4%	6.3%	9.1%
A	B	C	1.2%	1.5%	84.1%	13.3%
A	B	I	1.2%	1.5%	84.1%	13.3%

A	C	HA	69.2%	2.2%	14.1%	14.6%
A	C	H	6.1%	78.4%	6.3%	9.1%
A	C	C	1.2%	1.5%	84.1%	13.3%
A	C	I	1.2%	1.5%	84.1%	13.3%
A	D	HA	69.2%	2.2%	14.1%	14.6%
A	D	H	6.1%	78.4%	6.3%	9.1%
A	D	C	1.2%	1.5%	84.1%	13.3%
A	D	I	1.2%	1.5%	84.1%	13.3%
A	E	HA	69.2%	2.2%	14.1%	14.6%
A	E	H	6.1%	78.4%	6.3%	9.1%
A	E	C	1.2%	1.5%	84.1%	13.3%
A	E	I	1.2%	1.5%	84.1%	13.3%
B	A	HA	94.1%	2.4%	3.3%	0.1%
B	A	H	9.7%	84.4%	5.7%	0.1%
B	A	C	9.7%	84.4%	5.7%	0.1%
B	A	I	9.7%	84.4%	5.7%	0.1%
B	B	HA	93.4%	2.0%	3.9%	0.7%
B	B	H	4.6%	91.1%	3.7%	0.7%
B	B	C	0.3%	0.2%	98.6%	0.9%
B	B	I	48.4%	3.8%	36.9%	11.0%
B	C	HA	50.7%	2.8%	24.6%	21.9%
B	C	H	3.9%	70.0%	12.1%	14.0%
B	C	C	0.3%	0.3%	84.8%	14.6%
B	C	I	0.3%	0.3%	84.8%	14.6%
B	D	HA	50.7%	2.8%	24.6%	21.9%
B	D	H	3.9%	70.0%	12.1%	14.0%
B	D	C	0.3%	0.3%	84.8%	14.6%
B	D	I	0.3%	0.3%	84.8%	14.6%
B	E	HA	50.7%	2.8%	24.6%	21.9%
B	E	H	3.9%	70.0%	12.1%	14.0%
B	E	C	0.3%	0.3%	84.8%	14.6%
B	E	I	0.3%	0.3%	84.8%	14.6%
C	A	HA	91.0%	2.8%	6.1%	0.2%
C	A	H	5.3%	86.1%	8.4%	0.2%
C	A	C	0.8%	0.5%	98.6%	0.2%
C	A	I	57.1%	4.4%	36.7%	1.9%
C	B	HA	91.0%	2.8%	6.1%	0.2%
C	B	H	5.3%	86.1%	8.4%	0.2%
C	B	C	0.8%	0.5%	98.6%	0.2%
C	B	I	57.1%	4.4%	36.7%	1.9%
C	C	HA	89.8%	2.3%	7.0%	0.9%

C	C	H	2.5%	91.4%	5.3%	0.8%
C	C	C	0.1%	0.2%	98.8%	1.0%
C	C	I	12.0%	5.4%	50.0%	32.6%
C	D	HA	38.8%	2.6%	35.3%	23.3%
C	D	H	2.0%	65.4%	16.2%	16.5%
C	D	C	0.0%	0.3%	83.3%	16.3%
C	D	I	2.8%	3.0%	39.0%	55.3%
C	E	HA	38.8%	2.6%	35.3%	23.3%
C	E	H	2.0%	65.4%	16.2%	16.5%
C	E	C	0.0%	0.3%	83.3%	16.3%
C	E	I	2.8%	3.0%	39.0%	55.3%
D	A	HA	82.4%	4.3%	12.7%	0.6%
D	A	H	3.5%	85.2%	11.0%	0.3%
D	A	C	0.6%	0.3%	98.6%	0.6%
D	A	I	27.5%	7.0%	52.1%	13.5%
D	B	HA	82.4%	4.3%	12.7%	0.6%
D	B	H	3.5%	85.2%	11.0%	0.3%
D	B	C	0.6%	0.3%	98.6%	0.6%
D	B	I	27.5%	7.0%	52.1%	13.5%
D	C	HA	82.4%	4.3%	12.7%	0.6%
D	C	H	3.5%	85.2%	11.0%	0.3%
D	C	C	0.6%	0.3%	98.6%	0.6%
D	C	I	27.5%	7.0%	52.1%	13.5%
D	D	HA	79.0%	3.5%	14.3%	3.2%
D	D	H	1.6%	89.8%	7.0%	1.6%
D	D	C	0.0%	0.1%	97.5%	2.3%
D	D	I	1.8%	2.7%	22.5%	73.0%
D	E	HA	17.6%	2.0%	37.1%	43.3%
D	E	H	1.1%	54.1%	17.8%	27.0%
D	E	C	0.0%	0.1%	68.5%	31.4%
D	E	I	0.3%	1.0%	12.2%	86.4%
E	A	HA	1.4%	83.3%	12.8%	2.6%
E	A	H	1.4%	83.3%	12.8%	2.6%
E	A	C	0.1%	0.2%	95.8%	3.9%
E	A	I	13.4%	6.7%	31.3%	48.6%
E	B	HA	1.4%	83.3%	12.8%	2.6%
E	B	H	1.4%	83.3%	12.8%	2.6%
E	B	C	0.1%	0.2%	95.8%	3.9%
E	B	I	13.4%	6.7%	31.3%	48.6%
E	C	HA	1.4%	83.3%	12.8%	2.6%
E	C	H	1.4%	83.3%	12.8%	2.6%

E	C	C	0.1%	0.2%	95.8%	3.9%
E	C	I	13.4%	6.7%	31.3%	48.6%
E	D	HA	1.4%	83.3%	12.8%	2.6%
E	D	H	1.4%	83.3%	12.8%	2.6%
E	D	C	0.1%	0.2%	95.8%	3.9%
E	D	I	13.4%	6.7%	31.3%	48.6%
E	E	HA	59.8%	3.6%	17.6%	19.1%
E	E	H	0.6%	79.5%	7.3%	12.6%
E	E	C	0.0%	0.1%	85.5%	14.4%
E	E	I	0.3%	0.9%	4.9%	93.9%

5.4. Comprehensive Transition Matrix

A comprehensive transition matrix is constructed by synthesizing the LTCS model and the living arrangement model. The individual's new LTCS definition contains capitation rate level and living situation. Therefore, there are 20 (5×4) new statuses. Prior to using the new statuses, this research develops twenty-four (gender=2, living arrangement=4, and age level=3) transition matrixes, each with 30 (5×6) cells. After implementing the new status that combines LTCS and living arrangement, the number of matrixes declines to six (gender=2 and age level=3), but each with 420 (20×21) cells. The results are shown from Table 5-17 to Table 5-22.

The first column is the starting LTCS, and the second column is the starting living arrangement. Meanwhile, the first row is the ending LTCS, and the second row is the ending living arrangement. The results show that, although individuals have the same starting LTCS, the mortality rate increases for those who live in a nursing home or in community assisted living in the youngest and LTCS=A group. However, in the youngest group with the highest cost level (LTCS=E), living in community assisted living has a lower mortality rate compared to those who live at home alone or with help. Regardless of age, those living at home alone have the highest mortality rate compared to other living arrangements as they move into more impaired statuses. This result suggests that moving to a skilled LTC setting is recommended for those who are more impaired.

Individuals in the youngest age group and LTCS=A population are more likely to move out of nursing homes to community assisted living or home with helpers, but those in the oldest and LTCS=A population are more likely to stay in community assisted living or nursing homes. Females overall have a higher rate of staying in community assisted living or nursing homes than males because female life expectancy is higher. For the oldest population, living at home alone causes individuals to deteriorate faster. This finding suggests that a well-planned LTC setting can improve recovery rate and help to reduce health care costs.

This dissertation demonstrates that the tradeoff of including additional factors or including one unpredictable factor can increase the transition matrix size dramatically. This also demonstrates that the contribution of this dissertation, using a minimal number of additional factors to model the capitation rate level, is significant.

Table 5-17: Comprehensive Transition Matrix: Female 60-72

		A				B				C				D				E				Death
		HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	
A	HA	0.68	0.01	0.00	0.00	0.17	0.01	0.01	0.02	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.03
A	H	0.06	0.63	0.00	0.00	0.02	0.18	0.01	0.01	0.00	0.04	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.03
A	C	0.02	0.02	0.17	0.00	0.04	0.07	0.32	0.02	0.01	0.02	0.12	0.01	0.00	0.01	0.03	0.00	0.00	0.01	0.04	0.00	0.10
A	I	0.10	0.01	0.08	0.02	0.09	0.03	0.23	0.10	0.03	0.01	0.08	0.03	0.01	0.00	0.02	0.01	0.01	0.00	0.03	0.01	0.10
B	HA	0.11	0.00	0.00	0.00	0.60	0.02	0.01	0.00	0.10	0.01	0.02	0.02	0.03	0.00	0.01	0.01	0.02	0.00	0.00	0.00	0.04
B	H	0.02	0.10	0.00	0.00	0.04	0.58	0.01	0.00	0.01	0.11	0.01	0.01	0.00	0.04	0.00	0.00	0.00	0.02	0.00	0.00	0.04
B	C	0.02	0.00	0.04	0.00	0.01	0.01	0.47	0.00	0.01	0.01	0.25	0.01	0.00	0.00	0.08	0.00	0.00	0.00	0.03	0.00	0.05
B	I	0.02	0.00	0.04	0.00	0.24	0.03	0.18	0.04	0.06	0.02	0.14	0.06	0.02	0.01	0.05	0.02	0.01	0.00	0.02	0.01	0.05
C	HA	0.03	0.00	0.00	0.00	0.23	0.01	0.01	0.00	0.44	0.02	0.01	0.00	0.10	0.01	0.03	0.02	0.02	0.00	0.01	0.00	0.05
C	H	0.00	0.02	0.00	0.00	0.01	0.14	0.00	0.00	0.02	0.51	0.01	0.00	0.01	0.16	0.01	0.01	0.00	0.04	0.00	0.00	0.05
C	C	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.01	0.51	0.00	0.00	0.01	0.28	0.02	0.00	0.00	0.05	0.00	0.05
C	I	0.03	0.00	0.02	0.00	0.06	0.01	0.04	0.00	0.05	0.04	0.20	0.09	0.01	0.02	0.16	0.15	0.00	0.00	0.03	0.03	0.06
D	HA	0.02	0.00	0.00	0.00	0.07	0.01	0.00	0.00	0.18	0.02	0.01	0.00	0.45	0.03	0.03	0.01	0.03	0.01	0.02	0.04	0.07
D	H	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.14	0.01	0.00	0.01	0.56	0.02	0.00	0.00	0.13	0.02	0.02	0.06
D	C	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.11	0.00	0.00	0.01	0.62	0.00	0.00	0.00	0.16	0.02	0.06
D	I	0.01	0.00	0.02	0.00	0.01	0.01	0.02	0.00	0.03	0.01	0.06	0.01	0.01	0.03	0.14	0.30	0.00	0.01	0.04	0.19	0.09
E	HA	0.01	0.00	0.00	0.00	0.07	0.01	0.01	0.00	0.06	0.01	0.01	0.00	0.17	0.02	0.02	0.00	0.35	0.03	0.04	0.05	0.15
E	H	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.16	0.01	0.00	0.01	0.60	0.02	0.03	0.13
E	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.14	0.00	0.00	0.01	0.71	0.04	0.09
E	I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.04	0.04	0.00	0.02	0.05	0.62	0.19

Table 5-18: Comprehensive Transition Matrix: Female 73-85

		A				B				C				D				E				Death
		HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	
A	HA	0.65	0.01	0.01	0.00	0.15	0.01	0.02	0.02	0.03	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.05
A	H	0.07	0.60	0.01	0.00	0.02	0.16	0.01	0.01	0.00	0.04	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.05
A	C	0.02	0.01	0.30	0.00	0.03	0.03	0.34	0.05	0.01	0.01	0.12	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.02	0.00	0.02
A	I	0.02	0.01	0.30	0.00	0.04	0.03	0.26	0.11	0.02	0.01	0.09	0.04	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.01	0.02
B	HA	0.09	0.00	0.00	0.00	0.04	0.54	0.01	0.00	0.09	0.01	0.02	0.02	0.04	0.00	0.01	0.01	0.02	0.00	0.01	0.01	0.07
B	H	0.02	0.08	0.00	0.00	0.01	0.00	0.58	0.00	0.01	0.11	0.01	0.01	0.00	0.05	0.00	0.00	0.00	0.03	0.00	0.00	0.07
B	C	0.01	0.00	0.04	0.00	0.13	0.03	0.23	0.05	0.00	0.00	0.23	0.03	0.00	0.00	0.09	0.01	0.00	0.00	0.04	0.01	0.09
B	I	0.03	0.00	0.01	0.00	0.40	0.02	0.02	0.00	0.03	0.02	0.16	0.07	0.01	0.01	0.06	0.03	0.00	0.00	0.03	0.01	0.09
C	HA	0.02	0.00	0.00	0.00	0.16	0.01	0.01	0.00	0.44	0.02	0.02	0.00	0.09	0.01	0.04	0.03	0.03	0.00	0.01	0.01	0.09
C	H	0.00	0.01	0.00	0.00	0.01	0.09	0.00	0.00	0.02	0.48	0.01	0.00	0.01	0.15	0.02	0.02	0.00	0.06	0.01	0.01	0.08
C	C	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.48	0.00	0.00	0.00	0.26	0.04	0.00	0.00	0.07	0.01	0.08
C	I	0.01	0.00	0.02	0.00	0.03	0.01	0.04	0.00	0.02	0.03	0.21	0.09	0.01	0.02	0.16	0.15	0.00	0.01	0.05	0.05	0.09
D	HA	0.01	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.13	0.01	0.01	0.00	0.41	0.03	0.04	0.01	0.03	0.01	0.04	0.05	0.16
D	H	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.10	0.01	0.00	0.01	0.50	0.02	0.00	0.00	0.15	0.02	0.04	0.12
D	C	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.55	0.01	0.00	0.00	0.16	0.06	0.12
D	I	0.00	0.00	0.01	0.00	0.01	0.00	0.02	0.00	0.01	0.01	0.05	0.01	0.00	0.02	0.12	0.27	0.00	0.01	0.05	0.23	0.17
E	HA	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.04	0.00	0.01	0.00	0.12	0.01	0.02	0.00	0.38	0.04	0.06	0.08	0.21
E	H	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.10	0.01	0.00	0.01	0.62	0.03	0.05	0.17
E	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.56	0.08	0.21
E	I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.02	0.02	0.00	0.01	0.04	0.58	0.28

Table 5-19: Comprehensive Transition Matrix: Female >85

		A				B				C				D				E				Death
		HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	
A	HA	0.58	0.01	0.01	0.00	0.13	0.00	0.03	0.03	0.04	0.00	0.01	0.01	0.03	0.00	0.01	0.01	0.03	0.00	0.01	0.01	0.07
A	H	0.04	0.55	0.01	0.00	0.01	0.15	0.01	0.01	0.00	0.05	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.04	0.00	0.00	0.07
A	C	0.01	0.00	0.54	0.00	0.00	0.00	0.12	0.02	0.00	0.00	0.04	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.07	0.01	0.14
A	I	0.27	0.02	0.21	0.06	0.00	0.00	0.12	0.02	0.00	0.00	0.04	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.07	0.01	0.14
B	HA	0.08	0.00	0.00	0.00	0.46	0.01	0.02	0.00	0.08	0.00	0.04	0.03	0.05	0.00	0.02	0.02	0.03	0.00	0.01	0.01	0.12
B	H	0.01	0.07	0.00	0.00	0.03	0.45	0.01	0.00	0.01	0.12	0.01	0.02	0.00	0.07	0.01	0.01	0.00	0.04	0.00	0.01	0.12
B	C	0.00	0.00	0.03	0.00	0.00	0.00	0.33	0.00	0.00	0.00	0.23	0.04	0.00	0.00	0.13	0.02	0.00	0.00	0.06	0.01	0.15
B	I	0.03	0.00	0.00	0.00	0.16	0.01	0.12	0.04	0.05	0.01	0.13	0.08	0.03	0.01	0.07	0.05	0.01	0.00	0.03	0.02	0.15
C	HA	0.01	0.00	0.00	0.00	0.13	0.00	0.01	0.00	0.36	0.01	0.03	0.00	0.07	0.00	0.06	0.04	0.03	0.00	0.03	0.02	0.19
C	H	0.00	0.01	0.00	0.00	0.01	0.08	0.01	0.00	0.01	0.40	0.02	0.00	0.00	0.15	0.02	0.02	0.00	0.08	0.01	0.01	0.16
C	C	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.39	0.00	0.00	0.00	0.25	0.05	0.00	0.00	0.10	0.02	0.15
C	I	0.01	0.00	0.01	0.00	0.03	0.00	0.02	0.00	0.03	0.02	0.14	0.09	0.01	0.01	0.13	0.18	0.00	0.00	0.05	0.07	0.18
D	HA	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.12	0.01	0.02	0.00	0.34	0.01	0.06	0.01	0.03	0.00	0.05	0.06	0.25
D	H	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.09	0.01	0.00	0.01	0.43	0.02	0.01	0.00	0.15	0.03	0.05	0.18
D	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.47	0.01	0.00	0.00	0.17	0.08	0.19
D	I	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.02	0.01	0.04	0.01	0.01	0.01	0.08	0.25	0.00	0.00	0.04	0.26	0.25
E	HA	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.00	0.01	0.00	0.09	0.01	0.02	0.01	0.28	0.02	0.08	0.09	0.35
E	H	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.08	0.01	0.00	0.00	0.51	0.03	0.06	0.29
E	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.09	0.00	0.00	0.00	0.46	0.08	0.36
E	I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.02	0.00	0.01	0.03	0.55	0.36

Table 5-20: Comprehensive Transition Matrix: Male 60-72

		A				B				C				D				E				Death
		HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	
A	HA	0.67	0.01	0.00	0.00	0.15	0.01	0.01	0.01	0.04	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.05
A	H	0.06	0.62	0.01	0.00	0.02	0.16	0.01	0.01	0.00	0.04	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.05
A	C	0.02	0.02	0.16	0.00	0.03	0.05	0.27	0.01	0.01	0.02	0.11	0.01	0.00	0.01	0.03	0.00	0.01	0.01	0.05	0.00	0.19
A	I	0.09	0.01	0.07	0.01	0.07	0.02	0.19	0.08	0.03	0.01	0.07	0.03	0.01	0.00	0.02	0.01	0.01	0.00	0.03	0.01	0.19
B	HA	0.11	0.00	0.00	0.00	0.59	0.02	0.01	0.00	0.10	0.01	0.02	0.02	0.03	0.00	0.01	0.01	0.02	0.00	0.00	0.00	0.05
B	H	0.01	0.10	0.00	0.00	0.04	0.57	0.01	0.00	0.01	0.11	0.01	0.01	0.00	0.04	0.00	0.00	0.00	0.02	0.00	0.00	0.05
B	C	0.02	0.00	0.04	0.00	0.01	0.01	0.46	0.00	0.01	0.01	0.24	0.01	0.00	0.00	0.08	0.00	0.00	0.00	0.03	0.00	0.07
B	I	0.05	0.00	0.01	0.00	0.24	0.03	0.18	0.04	0.05	0.02	0.14	0.06	0.02	0.01	0.04	0.02	0.01	0.00	0.02	0.01	0.07
C	HA	0.03	0.00	0.00	0.00	0.22	0.01	0.01	0.00	0.43	0.02	0.01	0.00	0.09	0.01	0.03	0.02	0.02	0.00	0.01	0.00	0.08
C	H	0.00	0.02	0.00	0.00	0.01	0.13	0.01	0.00	0.02	0.49	0.02	0.00	0.01	0.15	0.02	0.02	0.00	0.03	0.00	0.00	0.07
C	C	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.01	0.50	0.00	0.00	0.01	0.28	0.02	0.00	0.00	0.05	0.00	0.07
C	I	0.03	0.00	0.02	0.00	0.06	0.01	0.04	0.00	0.05	0.04	0.20	0.09	0.01	0.02	0.15	0.15	0.00	0.00	0.03	0.03	0.08
D	HA	0.02	0.00	0.00	0.00	0.07	0.01	0.00	0.00	0.18	0.02	0.01	0.00	0.44	0.03	0.03	0.01	0.03	0.01	0.02	0.03	0.11
D	H	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.13	0.01	0.00	0.01	0.54	0.02	0.00	0.00	0.11	0.02	0.03	0.08
D	C	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.10	0.00	0.00	0.01	0.60	0.00	0.00	0.00	0.15	0.02	0.09
D	I	0.01	0.00	0.02	0.00	0.01	0.01	0.02	0.00	0.03	0.01	0.06	0.01	0.01	0.03	0.13	0.29	0.00	0.01	0.04	0.18	0.12
E	HA	0.01	0.00	0.00	0.00	0.06	0.01	0.01	0.00	0.06	0.01	0.00	0.00	0.16	0.02	0.01	0.00	0.33	0.03	0.03	0.04	0.20
E	H	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.14	0.01	0.00	0.01	0.55	0.03	0.04	0.18
E	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.13	0.00	0.00	0.01	0.69	0.04	0.12
E	I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.04	0.04	0.00	0.02	0.04	0.58	0.24

Table 5-21: Comprehensive Transition Matrix: Male 73-85

		A				B				C				D				E				Death
		HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	
A	HA	0.62	0.01	0.01	0.00	0.13	0.01	0.01	0.02	0.03	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.09
A	H	0.06	0.57	0.01	0.00	0.02	0.14	0.01	0.01	0.00	0.03	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.02	0.00	0.00	0.09
A	C	0.02	0.01	0.30	0.00	0.02	0.02	0.31	0.04	0.01	0.01	0.12	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.03	0.00	0.04
A	I	0.10	0.03	0.17	0.03	0.04	0.02	0.23	0.10	0.02	0.01	0.09	0.04	0.00	0.00	0.02	0.01	0.00	0.00	0.03	0.01	0.04
B	HA	0.09	0.00	0.00	0.00	0.55	0.02	0.01	0.00	0.09	0.01	0.02	0.02	0.04	0.00	0.01	0.01	0.02	0.00	0.01	0.01	0.09
B	H	0.01	0.08	0.00	0.00	0.04	0.53	0.02	0.00	0.01	0.10	0.01	0.02	0.00	0.04	0.01	0.01	0.00	0.02	0.00	0.00	0.09
B	C	0.01	0.00	0.03	0.00	0.01	0.00	0.42	0.00	0.00	0.00	0.22	0.03	0.00	0.00	0.09	0.01	0.00	0.00	0.04	0.01	0.12
B	I	0.01	0.00	0.03	0.00	0.13	0.03	0.22	0.04	0.03	0.02	0.15	0.07	0.01	0.01	0.06	0.03	0.00	0.00	0.03	0.01	0.12
C	HA	0.02	0.00	0.00	0.00	0.16	0.01	0.01	0.00	0.42	0.02	0.02	0.00	0.08	0.01	0.04	0.03	0.03	0.00	0.01	0.01	0.13
C	H	0.00	0.01	0.00	0.00	0.01	0.09	0.01	0.00	0.02	0.46	0.02	0.00	0.01	0.14	0.02	0.03	0.00	0.06	0.01	0.01	0.11
C	C	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.25	0.04	0.00	0.00	0.07	0.01	0.11
C	I	0.00	0.00	0.03	0.00	0.00	0.00	0.07	0.00	0.02	0.03	0.20	0.09	0.00	0.02	0.15	0.15	0.00	0.01	0.05	0.05	0.13
D	HA	0.01	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.12	0.01	0.01	0.00	0.38	0.03	0.04	0.01	0.03	0.01	0.03	0.05	0.22
D	H	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.09	0.01	0.00	0.01	0.47	0.03	0.01	0.00	0.13	0.03	0.05	0.16
D	C	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.52	0.01	0.00	0.00	0.15	0.06	0.17
D	I	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.01	0.01	0.05	0.01	0.00	0.02	0.11	0.25	0.00	0.01	0.04	0.21	0.23
E	HA	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.11	0.01	0.01	0.00	0.35	0.04	0.06	0.07	0.27
E	H	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.09	0.01	0.00	0.01	0.56	0.04	0.07	0.22
E	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.52	0.08	0.27
E	I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.02	0.02	0.00	0.01	0.04	0.52	0.35

Table 5-22: Comprehensive Transition Matrix: Male >85

		A				B				C				D				E				Death
		HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	HA	H	C	I	
A	HA	0.54	0.01	0.01	0.00	0.11	0.00	0.02	0.02	0.04	0.00	0.01	0.01	0.03	0.00	0.01	0.01	0.04	0.00	0.01	0.01	0.13
A	H	0.04	0.51	0.01	0.00	0.01	0.12	0.01	0.01	0.00	0.04	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.04	0.00	0.01	0.13
A	C	0.01	0.00	0.46	0.00	0.00	0.00	0.09	0.01	0.00	0.00	0.03	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.08	0.01	0.24
A	I	0.01	0.00	0.46	0.00	0.00	0.00	0.09	0.01	0.00	0.00	0.03	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.08	0.01	0.24
B	HA	0.07	0.00	0.00	0.00	0.44	0.01	0.02	0.00	0.08	0.00	0.04	0.03	0.05	0.00	0.02	0.02	0.02	0.00	0.01	0.01	0.15
B	H	0.01	0.07	0.00	0.00	0.02	0.43	0.02	0.00	0.01	0.11	0.02	0.02	0.00	0.07	0.01	0.01	0.00	0.03	0.01	0.01	0.15
B	C	0.00	0.03	0.00	0.00	0.00	0.00	0.31	0.00	0.00	0.00	0.22	0.04	0.00	0.00	0.12	0.02	0.00	0.00	0.05	0.01	0.19
B	I	0.00	0.03	0.00	0.00	0.15	0.01	0.12	0.03	0.00	0.00	0.22	0.04	0.00	0.00	0.12	0.02	0.00	0.00	0.05	0.01	0.19
C	HA	0.01	0.00	0.00	0.00	0.12	0.00	0.01	0.00	0.33	0.01	0.03	0.00	0.06	0.00	0.06	0.04	0.03	0.00	0.03	0.02	0.25
C	H	0.00	0.00	0.00	0.00	0.00	0.07	0.01	0.00	0.01	0.37	0.02	0.00	0.00	0.12	0.03	0.03	0.00	0.07	0.02	0.02	0.22
C	C	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.37	0.00	0.00	0.00	0.23	0.05	0.00	0.00	0.09	0.02	0.21
C	I	0.01	0.00	0.01	0.00	0.03	0.00	0.02	0.00	0.03	0.01	0.13	0.09	0.01	0.01	0.12	0.17	0.00	0.00	0.05	0.07	0.24
D	HA	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.11	0.01	0.02	0.00	0.30	0.01	0.05	0.01	0.02	0.00	0.05	0.06	0.33
D	H	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.08	0.01	0.00	0.01	0.39	0.03	0.01	0.00	0.12	0.04	0.06	0.25
D	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00	0.43	0.01	0.00	0.00	0.16	0.07	0.26
D	I	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.03	0.01	0.01	0.01	0.07	0.23	0.00	0.00	0.03	0.23	0.33
E	HA	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.09	0.01	0.00	0.24	0.01	0.07	0.08	0.43
E	H	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.07	0.01	0.00	0.00	0.43	0.04	0.07	0.37
E	C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.40	0.07	0.44
E	I	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.03	0.48	0.44

Chapter 6. **Analytical and Simulated Projections**

The aim of this chapter is to apply the developed model to create projections. This chapter discusses both analytical and simulated projections. Analytical projections provide average population and cost forecasting, and simulated projections can explain the variations in expected outcomes. These variations provide information regarding the possible range of expected outcomes. The variations derived from simulations are useful for quality measurements. The detail of both sets of results will be discussed below.

In order to illustrate how the developed model forecasts future LTC demand and cost, two hypothetical Managed Care Organizations (MCOs) are created based on current WI LTC managed care program enrollees' characteristics. This research randomly selects 500 enrollees as recipients in MCO A, and 2000 enrollees as recipients in MCO B. This research decides to make the two hypothetical MCO sizes significantly different because this helps us to understand how expected outcomes vary based on differences in size. The given information about individual enrollees includes gender, current LTCS (capitation rate level), age, and current living arrangement. The following sections will discuss the projection results for both MCOs and the corresponding implications.

The major difference between the two MCOs is the number of recipients. Comparing the projected results from these two typical sizes of MCOs provides relevant information for government regarding quality measurements and budget planning which will be discussed below.

Both MCOs share approximately the same gender distribution, but the population of MCO B is 1.5 years older on average than the MCO A population. The starting LTCS structures are evenly distributed for both MCOs, and both share the same distribution for living arrangement as well. Table 6-1 displays the characteristics for both MCOs. The following discussion will be based on these two MCOs.

Prior to conduct a forecasting analysis, this research categorizes age into three levels: 60-72, 73-85, and >85. The LTCS transition rate is constant within each age range. In order to provide more meaningful forecasting, this research implements a piecewise linear curve to re-estimate the transition rate at age as a continuous variable. The details of piecewise linear function are described in Appendix A.

Table 6-1: Characteristics of hypothetical MCOs

		MCO A	MCO B
Total enrollees		500	2,000
Gender			
	Female	358 (72%)	1426 (71%)
	Male	142 (28%)	574 (29%)
Age		73.67	75.13
	60-72	241 (48%)	813 (41%)
	73-85	196 (39%)	888 (44%)
	85+	63 (13%)	299 (15%)
LTCS			
	A	95 (19%)	320 (16%)
	B	100 (20%)	437 (22%)
	C	93 (19%)	366 (18%)
	D	103 (21%)	488 (25%)
	E	103 (21%)	380 (19%)
Living Arrangement			
	Home Alone (HA)	151 (31%)	587 (29%)
	Home with Helpers (H)	112 (23%)	478 (24%)
	Community Assisted Living (C)	87 (18%)	287 (14%)
	Nursing Home (I)	41 (8%)	151 (8%)

6.1. Analytical Projections

6.1.1. Analytical closed cohort projections over 10 years for MCO A

The starting population structure for MCO A is displayed in Table 6-1. The fitted transition rate matrix is applied to estimate the next year's LTCS for individuals. Figure 6-1shows an accumulated percentage graph for these estimates and the x-axis represents the year. The difference between the two lines represents the percentage of upper category. For example, the difference between LTCS=A and LTCS=B represents how much LTCS=B increases on top of LTCS=A. That is, in the first year, the percentage of the total population in LTCS=A is approximately 17%, and the percentage of LTCS=A and LTCS=B together is approximately 36%. Therefore, the percentage of LTCS=B individually is about 19% (36%-17%).

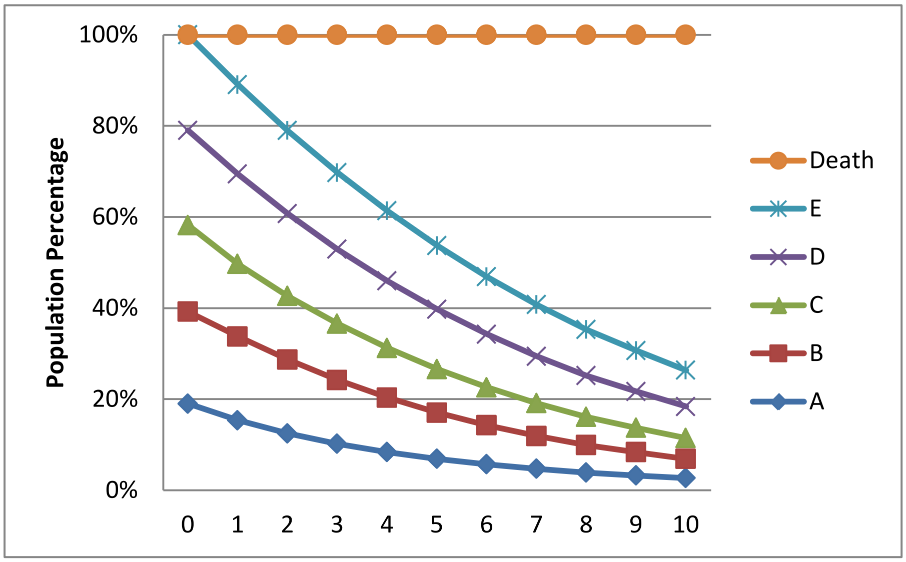

Figure 6-1: Analytic Closed Cohort Projections Over 10 Years for MCO A

The starting LTCS is distributed evenly across five different statuses. After one year, 55 out of 500 enrollees die. The entire closed cohort shrinks in 10 years; approximately 26% of the original population remains in the cohort after 10 years, which implies that 74% of population dies in 10 years. The percentage of the population at low capitation rate levels decreases, and overall the entire remaining population shifts to higher capitation rate categories such as LTCS=D or E.

This research also forecasts living arrangement trends, as shown in Figure 6-2, and it is notable that the percentage of the population living in nursing homes remains stable at 10% over the course of 10 years. Because the nursing home population has a higher risk of passing away in the next year, the deceased former nursing home residents will no longer affect the percentages of the total population in different living arrangements. However, the percentage of the population that requires community assisted living increases from 26% to 43%. This rise in community assisted living corresponds with an 11% drop in the percentage of the population living at home alone and a 7% drop in the percentage of the population living at home with helpers. These two populations mostly switch to LTC settings with higher-skilled care. These results suggest that institutions and governments would benefit from additional advanced LTC facility planning. For example, more beds may be required in community assisted living, and nursing homes may need to employ more RNs or nurses' aides.

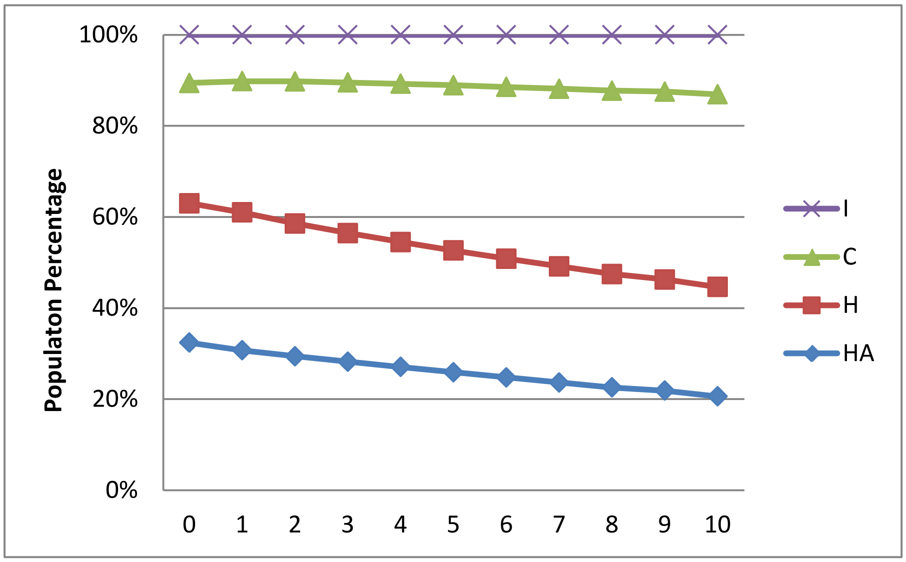

Figure 6-2: Living Arrangement Closed Cohort Analytical Projection over 10 Years for MCO

A linear regression is estimated for the average capitation rate over 10 years in MCO A (displayed in Figure 6-3). Over 10 years, the monthly average cost increases from $2,125 to $3,166, and the average monthly growth is $103 annually per person without accounting for inflation. In sum, the MCO A population is expected to have a higher average monthly capitation rate, more impaired health conditions, and more individuals staying in community assisted living after 10 years.

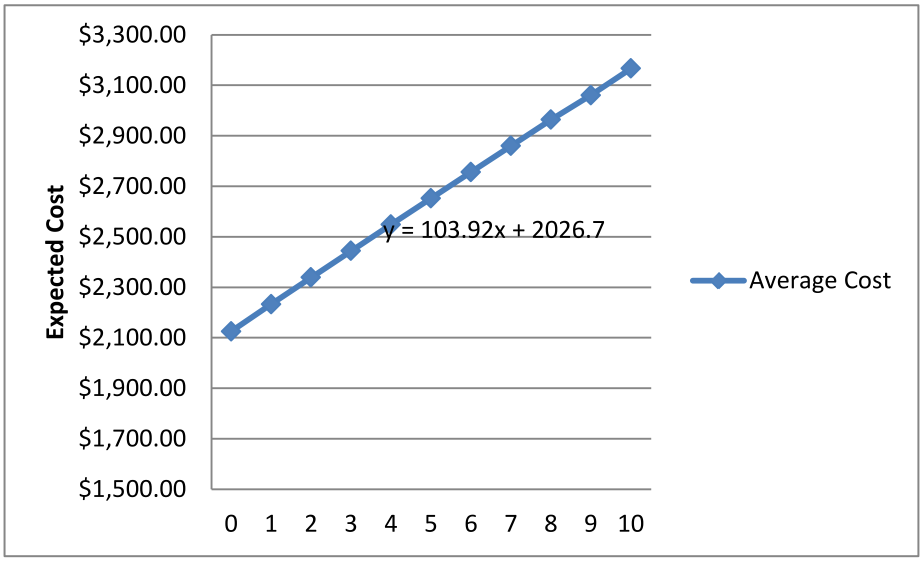

Figure 6-3: Average Cost Closed Cohort Analytical Projection over 10 Years for MCO A

6.1.2. Analytical closed cohort projections over 10 years for MCO B

Figure 6-4 describes the annual LTCS distribution over 10 years for MCO B. The population of MCO B is four times bigger than that of MCO A. This research forecasts the population structure in this closed cohort over 10 years. The 10-year mortality rate for MCO B is 3% higher than the MCO A mortality rate; only 23% of the closed cohort remains in MCO B after 10 years. The overall annual LTCS structure at each year shares a similar distribution with MCO A. These results indicate that the expected LTCS transition patterns are not dramatically affected by the size of the MCO.

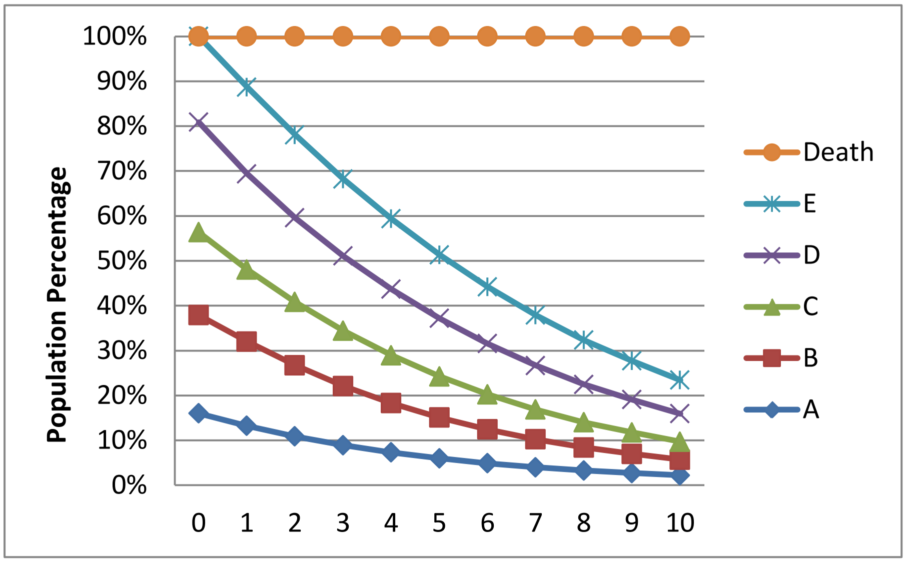

Figure 6-4: Analytic Closed Cohort Projections Over 10 Years for MCO B

The percentage of the MCO B population living at home alone decreases from 32% to 18% over 10 years, and the population living at home with helpers also shrinks approximately 10% throughout the projection period. Meanwhile, the percentage of the population in community assisted living grows from 27% to 44%, and the nursing home population increases from 9% to 15%. The details are shown in Figure 6-5. Comparing the expected living arrangement results between the two MCOs, the percentage of the population in dependent living arrangements (i.e., nursing homes and community assisted living) is growing somewhat faster in MCO B than in MCO A.

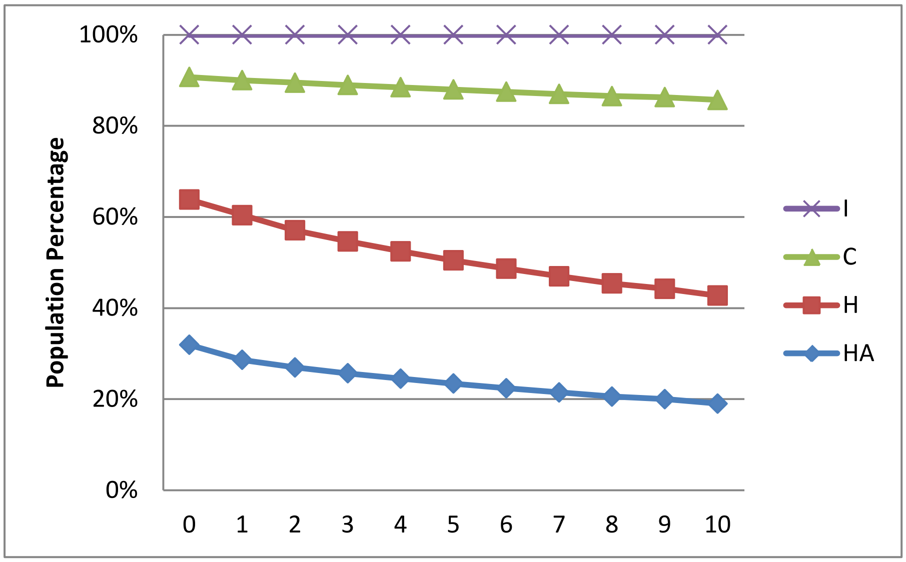

Figure 6-5: Living Arrangement Closed Cohort Analytical Projection over 10 Years for MCO B

As mentioned previously, the population in MCO B switches to a highly dependent care setting faster than the MCO A population. The care setting is an essential factor for the average monthly cost. Figure 6-6 shows the trend of average monthly cost throughout the projection period for MCO B. The monthly average cost grows $108 over 1 year, which is $5 more than the monthly per person growth of MCO A. The average monthly cost increases from $2,140.81 to $3,227.76 over 10 years.

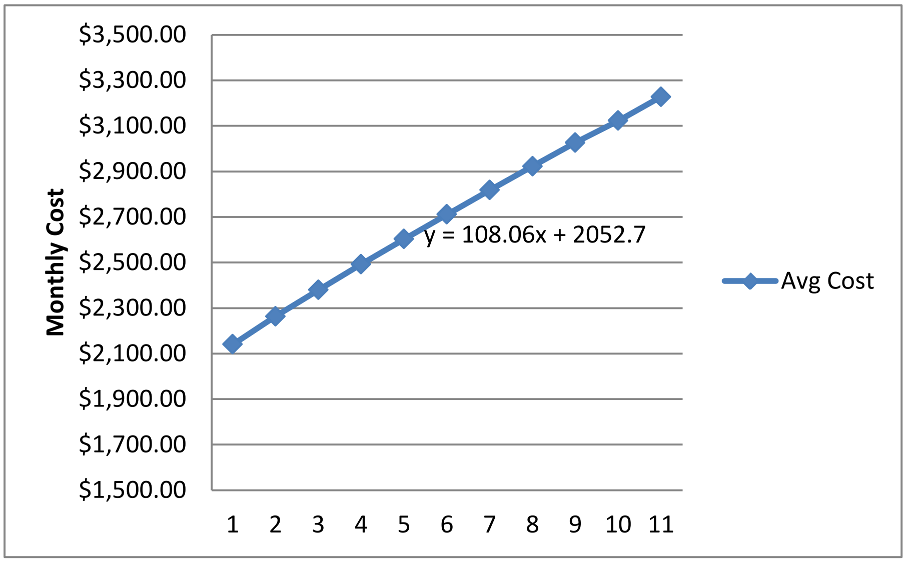

Figure 6-6: Average Cost Closed Cohort Analytical Projection over 10 Years for MCO B

The expected results for the two MCOs are not dramatically different. This is caused by design. We randomly selected members for each MCO. The expected migration in LTCS and living situation is due entirely to the minor differences in starting characteristics resulting from the random sampling. It makes no sense to compare the progression of expected results for the two MCO's. What does differ between the two MCOs is how likely their actual migration results are to differ from their expected migration results. The larger MCO should be less like to deviate dramatically from the expected path. The conclusion here is that MCO size has no impact on expected average migration. We need simulation to demonstrate that size does affect the level of variation.

A more complete understanding of reasonable variations among capitation rate levels and living arrangements can not only help government to set up new capitation rates for future LTC enrollees but also provide a reference for MCO quality measurement. Thus, conducting simulated projections is recommended. The simulated projections results for both MCOs will be presented and discussed in the following sections.

6.2. Simulated Projections

Although analytical projection results provide expected outcomes for both MCOs throughout the 10-year period, several questions regarding the variation of excepted outcomes are extremely difficult to address through analytical projections alone. Variations of expected outcomes derived from analytical projections provide essential perspectives on the need for future simulation processes. Additionally, knowledge of the possible variations can provide rigorous support for policy recommendations regarding budget planning and quality measurements. Thus, conducting simulation modeling is suggested. Simulation modeling is an essential method for both small and large populations to inform policy makers in the provision of health care. Simulation modeling has been widely applied to health care-related problems. Therefore, the aim of this step is to demonstrate simulated projections in order to provide greater insight into possible variations than analytical projections could provide by themselves. Simulation results allow us to determine whether an observed deviation from expected results is unusual or within a range anticipated for similar simulated MCOs.

This research conducts 100 simulations for each MCO to compute the variance of expected outcomes. The results of the simulation analysis will be discussed in the following sections.

The 10-year analytical projections in MCO A and MCO B were discussed in chapter 6.1. Table 6-2 describes the expected probability and corresponding standard deviation among the living population derived from 100 simulations of each ending LTCS over a 10-year period. On average, MCO A has a 2 times higher standard deviation than MCO B, because MCO A has a relatively smaller size.

Although the standard deviations for both MCOs are not dramatically large, the impacts of the variations could make a tremendous difference within each MCO. For example, the standard deviation of the average monthly cost per person for MCO A in the first year is $28.14, which means that 95% of the simulated results would be between $2,181.54$\pm(2 \times \$28.14)$. $56.28 (2.6% of average cost) per person per month contributes a total of $28,140 ($56.28×500) per month to MCO A. In addition, this variation contributes ±\$293,638 (\$28,140×12×0.88) among living population in the first year. For MCO B, the variations can contribute ±\$678,439 among living population in the first year. Suppose the marginal profit for MCO B is assumed to be 5% of the total capitation rate (\$2,256.59×12×2000×0.8895×0.05=\$2,408,684). The amount of the variations is approximately 28% the company's annual marginal profit in MCO B. Therefore, if the MCO is capable of keeping the lowest boundary of average cost, the marginal profit of the business will grow greatly. The variation in average cost for MCO B is about half that of MCO A. If both have a 5% profit margin with expected costs, than MCO A is much more likely to experience a loss due to random variation in costs from expected values. The impact of the variations will be intensified in bigger MCOs and over longer periods of time.

Table 6-2: Analytical and simulated results

		MCO A		MCO B	
		Mean	Standard Deviation	Mean	Standard Deviation
1st Year					
	A	14.00%	1.12%	13.30%	0.60%
	B	22.60%	1.53%	18.45%	0.90%
	C	14.60%	1.44%	17.05%	0.87%
	D	19.00%	1.52%	21.20%	0.80%
	E	17.80%	1.42%	18.95%	0.86%
	Death	12.00%	1.39%	11.05%	0.68%
	Average Cost	$2,181.54	$28.14	$2,256.59	$15.89
2ed Year					
	A	13.00%	1.58%	11.25%	0.80%
	B	16.00%	1.71%	15.85%	5.93%
	C	12.20%	1.89%	13.85%	0.79%
	D	17.20%	2.04%	18.60%	0.90%
	E	18.80%	1.77%	18.65%	1.03%
	Death	22.80%	1.74%	21.80%	0.89%
	Average Cost	$2,343.89	$35.87	$2,376.40	$21.91
3rd Year					
	A	12.20%	1.72%	9.45%	0.88%
	B	11.80%	1.88%	13.05%	1.07%
	C	10.00%	1.92%	11.90%	1.12%
	D	16.80%	2.49%	17.10%	1.29%
	E	18.00%	2.13%	16.60%	1.30%
	Death	31.20%	1.98%	31.90%	1.07%
	Average Cost	$2,471.81	$48.30	$2,476.12	$22.01
4th Year					
	A	7.20%	2.01%	8.45%	0.70%
	B	12.60%	2.24%	10.10%	0.72%
	C	8.60%	2.03%	10.00%	0.87%
	D	15.20%	2.41%	15.50%	0.95%
	E	15.00%	2.45%	15.10%	1.05%
	Death	41.40%	2.05%	40.85%	1.04%
	Average Cost	$2,576.70	$56.04	$2,583.18	$29.31
5th Year					
	A	5.20%	1.99%	6.50%	1.09%

	B	11.40%	2.22%	8.45%	1.08%
	C	8.20%	2.37%	9.60%	1.32%
	D	11.00%	2.65%	13.35%	1.61%
	E	14.00%	2.80%	13.95%	1.70%
	Death	50.20%	2.24%	48.15%	1.04%
	Average Cost	$2,677.19	$65.42	$2,702.06	$33.54
6th Year					
	A	5.20%	2.31%	4.95%	1.09%
	B	9.60%	0.26%	8.00%	1.39%
	C	6.40%	1.49%	7.40%	1.47%
	D	8.60%	1.45%	11.95%	1.76%
	E	14.20%	1.54%	13.05%	2.16%
	Death	56.00%	2.25%	54.65%	1.09%
	Average Cost	$2,798.95	$65.40	$2,825.14	$36.55
7th Year					
	A	5.60%	2.33%	3.85%	1.10%
	B	5.20%	2.45%	6.30%	1.48%
	C	8.20%	2.61%	6.25%	1.20%
	D	8.60%	2.98%	10.65%	1.96%
	E	12.20%	2.95%	11.25%	2.10%
	Death	60.20%	2.07%	61.70%	1.00%
	Average Cost	$2,888.51	$70.99	$2,940.68	$40.63
8th Year					
	A	4.40%	2.43%	3.45%	1.07%
	B	4.60%	2.74%	5.10%	1.53%
	C	6.80%	2.74%	5.70%	1.53%
	D	8.20%	3.20%	8.85%	2.20%
	E	10.80%	3.29%	8.75%	2.34%
	Death	65.20%	1.93%	68.15%	0.95%
	Average Cost	$3,002.12	$89.72	$2,967.00	$44.41
9th Year					
	A	2.80%	2.65%	2.35%	0.40%
	B	5.00%	2.68%	4.55%	0.47%
	C	5.40%	2.90%	5.15%	0.57%
	D	9.60%	3.54%	6.60%	0.67%
	E	8.40%	3.44%	8.40%	0.64%
	Death	68.80%	1.75%	72.95%	0.96%
	Average Cost	$3,077.78	$98.79	$3,108.57	$46.23
10th Year					
	A	2.20%	2.58%	2.05%	1.41%
	B	3.60%	2.31%	3.70%	1.39%

C	5.00%	3.28%	3.40%	1.92%
D	7.40%	3.51%	5.90%	2.36%
E	7.60%	3.57%	7.30%	2.09%
Death	71.00%	1.65%	74.90%	0.88%
Average Cost	$3,209.47	$115.70	$3,229.79	$52.20

6.2.1. 10-Year Variations

Simulation analyses provide a guideline for policy makers to evaluate the performance of MCOs. Actual outcomes above or below the simulation analysis range deserve further analysis. In addition, simulation analysis can be used to set up a feedback and reward system for both MCOs and government managers, while providing a rigorous evaluation system over time.

This research demonstrates both MCOs' 10-year variations related to population structure and average monthly cost per person. Figure 6-7 describes the variations among 100 simulations in the tenth year in MCO A. The left-sided y-axis represents the percentage of population LTCS structure in tenth years. The right-sided y-axis represents the monthly cost per person. The x-axis represents the simulation events. The probability of LTCS=A, B, C, D, and E is calculated among the living population, and the probability of mortality is calculated among the total starting population (500). The magnitude of variation increases as the cost level increases. The variation for LTCS=C, D, and E jumps up and down. Compared to the population structure among the total living population, the mortality variation in 100 simulations is relatively stable.

Figure 6-8 describes the results of 100 simulations for MCO B. It indicates that the variations related to both population structure and average cost are relatively stable compared to MCO A. Figure 6-7 and Figure 6-8 illustrate a range of reasonable expectations for the performance of both MCOs. The simulated range of results more importantly provides a basis for judging actual results for each MCO. If both experience 70% mortality, Figure 6-7 would judge MCO A's performance as "average" or "as expected", while Figure 6-8 would judge MCO B's performance as "better than expected".

6.2.2. Average Years in Institutional Care Setting

As discussed previously, living arrangement is highly correlated with LTCS (cost level), and those who live in nursing homes are assumed to be the most dependent population. Nursing home populations usually use more health care resources, including medical resources and workforce, from payers' and administrators' perspectives, so this population typically has higher expected LTC costs than populations in other living situations; moreover, individuals in LTC programs are more likely to stay in nursing homes due to health conditions. Thus, efficiently reducing the amount of time that individuals live in nursing homes can save health care resources. It is important to understand the average number of years spent outside of a nursing home within the 10-year projection period used in this study.

This research conducts simulation analysis to understand the average number of nursing-home-free years among living individuals within the 10-year projection period. Figure 6-9 shows the results for both MCOs over 100 simulations. Due to its small size, MCO A has higher variations of nursing-home-free years among individuals, and it varies from 4.5 years to 5.1 years. MCO B varies from 4.39 years to 4.7 years. From the MCO perspective, reducing the years spent in nursing homes can not only increase the organization's marginal profit, but also represents the improvement of individuals' health conditions and independence. These results provide a useful point of reference for business strategy and facility planning. For example, an advanced understanding of nursing-home-free years helps nursing home administrators to prepare enough beds or recruit enough RNs.

6.3. Managed Care Organization Performance Measurement

The aim of conducting simulation projections is to help managers and payers fully understand the expected outcomes, typical variations from these expected values, and to evaluate the quality of the LTC delivery system over time. This research shows the variations for population cost level structure, mortalities, average monthly cost, and average years living outside of a nursing home. All of these factors can be very effective quality measurements, but evaluating actual MCO performance requires more case-by-case analysis. For example, one MCO has an unexpectedly low average monthly cost, but it is paired with a very high mortality rate. Can policy makers jump to any conclusions about the MCO's performance based only on these two data points? On the other hand, from the care providers' perspective, is unconditionally prolonging a recipient's life at the highest cost level status recommended? Will recipients' quality of life be taken into account for quality of care measurement? The conflict between payers' financial goals and care recipients' quality of life goals is a perpetual challenge when evaluating the quality of health care.[75]

The Healthcare Effectiveness Data and Information Set (HEDIS) has been used widely by consumers to compare health care plans and care performance. However, HEDIS measurements do not account for all aspects of quality of care.[76,77] Moreover, many studies have not confirmed that HEDIS indicators are associated with better health quality or outcomes in some situations.[78,79] Refining existing measures is recommended.[77,80] Measuring MCO performance needs to consider both business and quality of life perspectives. This research can be a very useful tool that is able to collaborate with the HEDIS to measure MCO or health plan performance.

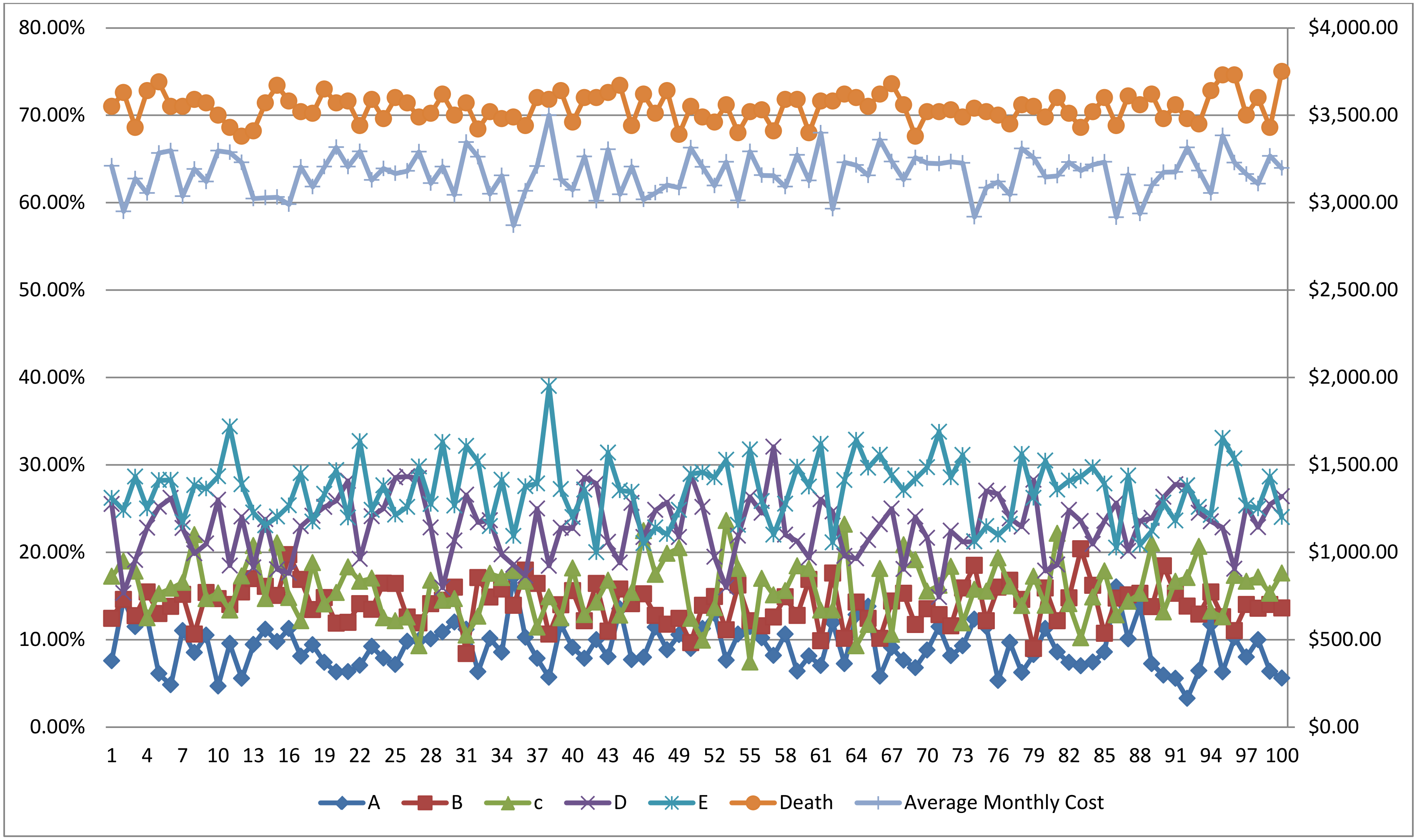

Figure 6-7: 10th Year population structure and cost variations at MCO A

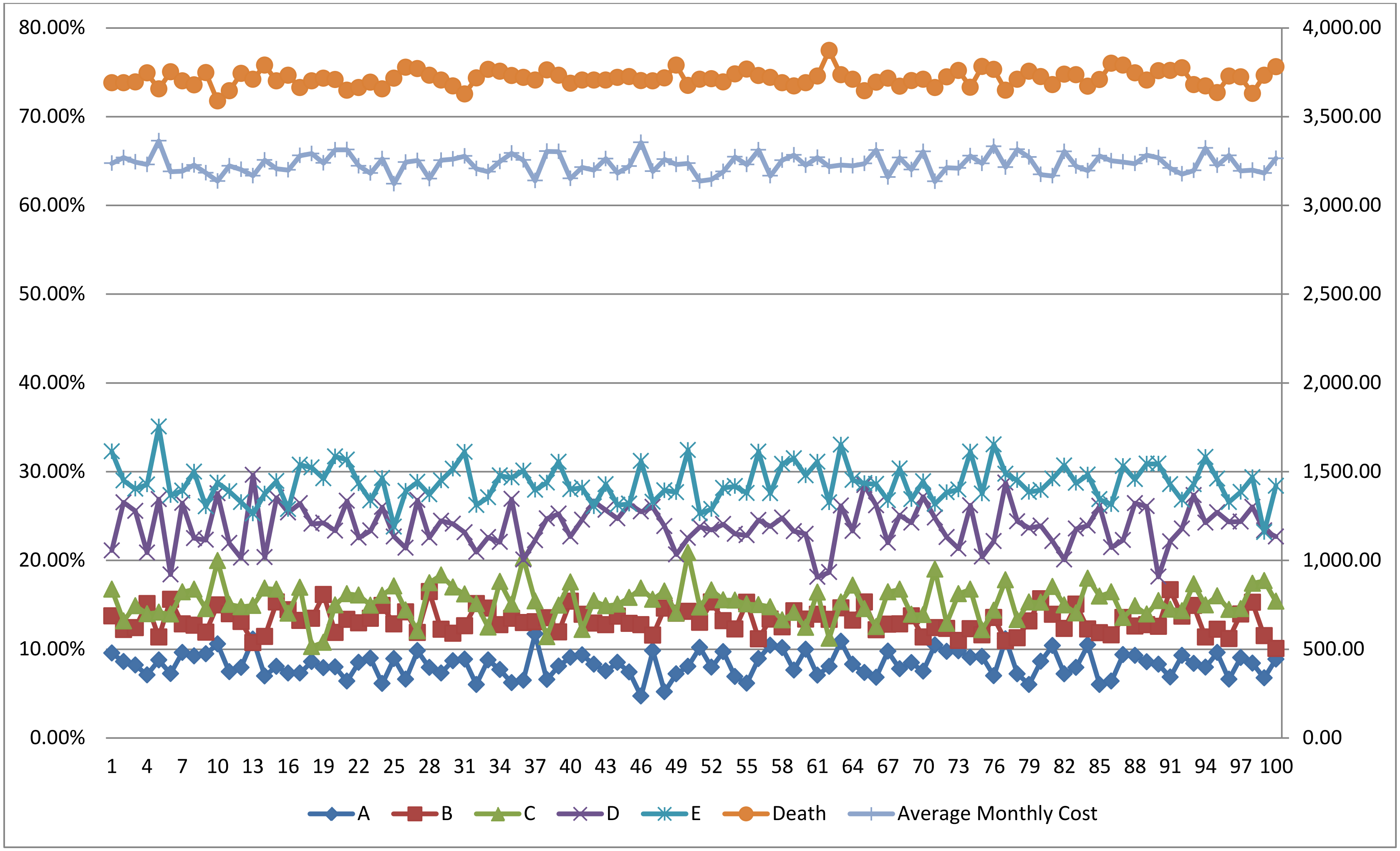

Figure 6-8: 10th Year population structure and cost variations at MCO B

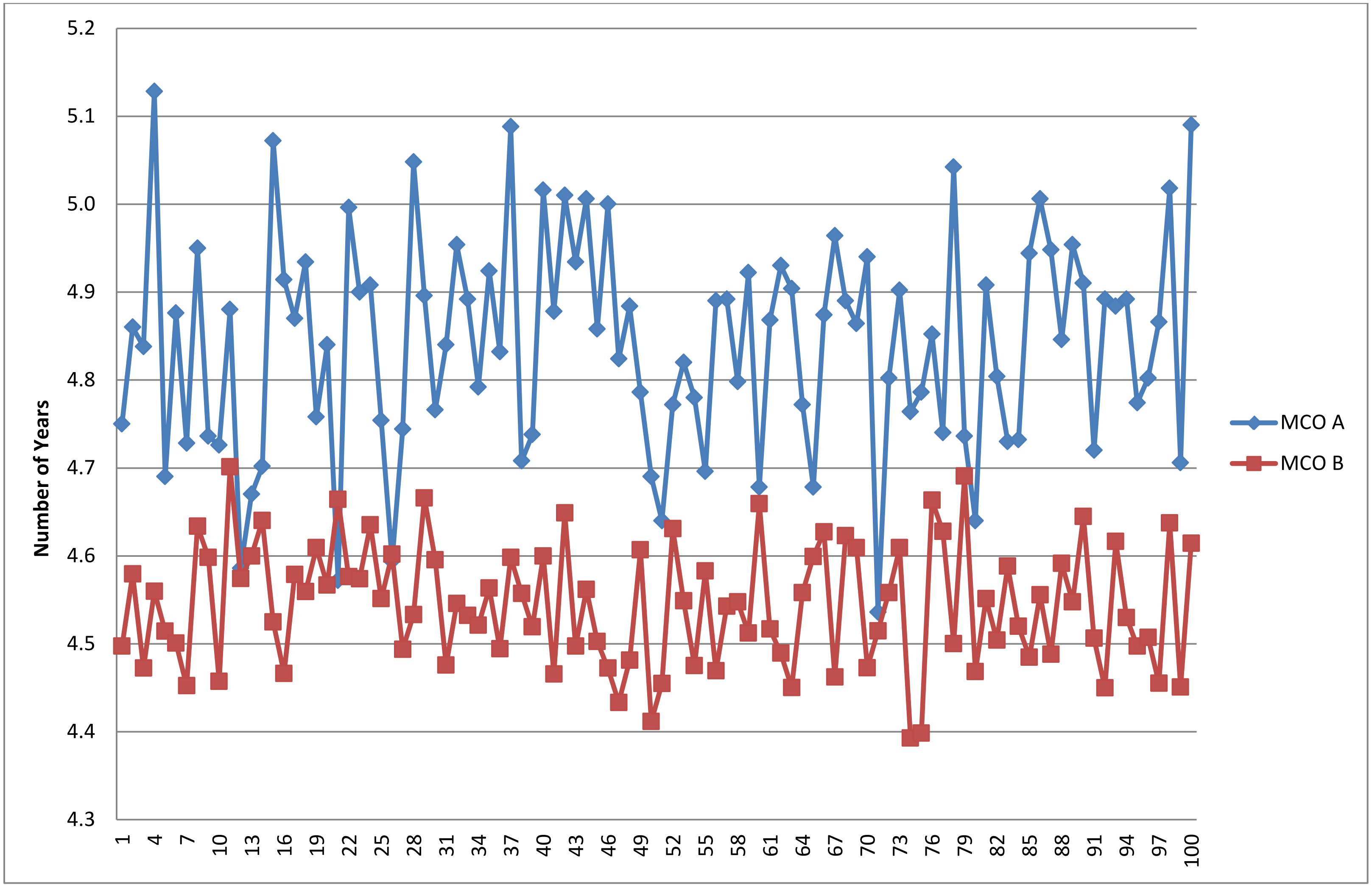

Figure 6-9: Average Number of live Years without Living in Nursing Home from 100 Simulations

Chapter 7. **Discussion**

This dissertation contributes to health system engineering state-space research. It demonstrates a sequence of procedures for identifying factors to improve the ability to predict future LTC capitation rates. In addition, it proposes a methodological approach to scientifically simplify the parametric forms of status transition. It addresses the ability to predict the future capitation rate level of individuals as well as populations, which has a direct impact on governments' budgets and LTC facility planning. Last but not least, this research demonstrates the applications of the developed model, simulates the possible MCO's financial burden/outcomes, and suggests the new indicators for quality measures. This chapter summarizes the main results of the research and discusses the limitations of this dissertation. Possible applications and future research directions are presented at the end of this chapter.

7.1. Summary of Research Results

First, this study demonstrates the complexity of identifying additional variables to model LTCS transition. The number of statistical tests combined with reasonable interaction terms increases dramatically as the number of independent variable included in the model grows. Gender, age, and current living situation are all valid variables that can explain variations in movement between LTC statuses. Although initially the impact of gender is only statistically significant on future capitation rate level and death for those who start at the lowest cost level (LTCS=A), this research keeps the gender impact on ending LTCS=Death throughout all starting LTCS, based on expert opinions and US life table that have demonstrated gender's impact on mortality rate. For individuals with more impaired starting LTCS, knowing their gender does not improve the power to predict their next capitation rate level, but it does enhance the ability to predict the chance of death in next year. Meanwhile, age and current living situation can more fully explain variations in transition between statuses. Overall, the probabilities of recovery decrease as age increases, and the risk of death increases as age increases. Although living in community assisted living or in an institutional facility (i.e., nursing home) is correlated with higher requirements for health services or more impaired health conditions, the mortality rate is not necessarily higher, especially for the higher-cost starting statuses. This is probably the case because living with medical professionals can effectively prevent death and also slow down deterioration speed.

Second, this research addresses the relationship between current status and future status. Instead of using the same LTCS as a point of reference group for multinomial logistic regression analysis throughout all starting LTCS, this research emphasizes the difference between statuses. Therefore, this research fits the model individually and re-codes the dependent variables. For example, “-1” represents that an individual deteriorates one level from his or her starting status and vice versa. This approach takes the relationship between statuses into account and provides more understandable and deliverable information for modeling the change in LTCS results in a more parsimonious model formant.

Third, this study proposes a flexible and simple parametric format for the purpose of future health status modeling. Currently, there are many available published approaches to handle sparse sample problem while building the model. This dissertation adopts one of them. Given identified explanatory variables, this research codes them cumulatively based on LTC recipients’ ability of being independent. The reference group is the most independent category, i.e., the youngest individuals who live at home alone. The cumulative code allows this research to overcome the limitations of SAS Catmod procedure default setting. Moreover, it provides a scientific and convenient approach to grouping sparse samples with reasonably adjacent groups; testing these additional adjustments reduces the statistically required estimations. Thus, this approach provides a valid and reasonable methodology to reduce the total number of required parameters. For example, the original transition model needs 600 estimations, but the developed model only needs 153 estimations (approximately one-quarter of the original total) to capture the transition characteristics for the entire population. Cumulative codling also facilitates search for parsimonious model and addresses sparse data issues.

Fourth, this research confirms that living arrangements are highly correlated with individuals' ability of being independent. Living arrangement is a significant factor. A transition model for living arrangement is also developed. The explanatory variables for living arrangement are current capitation rate (LTCS), gender, age, and the relationship between current and future capitation rate. The final LTCS transition model incorporates the fitted results of living arrangement among individuals. Thus the final model synthesizes the results of the two fitted models to estimate the most precise transition rates, and a new definition of individual status is based on capitation rate level (LTCS) and current living arrangement.

Fifth, the developed model is validated. The validation process is divided into two parts: external validation and cross-sectional validation. Comparing male and female mortality rates to match published life tables is a suitable approach to measure external validity. For prediction performance of developed model, the actual transition rate of the validation dataset (2010-2011) is not compared to the fitted transition rate derived from the developed model directly. Instead, a sequence of validation tests is designed. The hypothesis of consistency between the two datasets is not rejected, and the hypothesis of expected transition rate between the validation dataset and the model construction dataset is not rejected as well. According to the validation of prior key results using additional year of data, and the processes demonstrate techniques for testing assumption

Sixth, this study presents analytical and simulated projections. Simulated projections provide the variations of the analytical projection results. This part of the research shows that utilizing the transitional model developed by this research can provide projections of metrics of interest (mortality, costs, years of non-instutionalized life, etc.) along with simulation based-assessments of the anticipated level of variation of actual results about these projections. This part demonstrates use of analytic and simulation techniques, and provides basis for projecting future population characteristics and demand for LTC services (budgeting) and for assessing actual experience.

Last, this research suggests new potential quality indicators for managed care organizations. The simulation results provide a range of expected outcomes for different sizes of MCOs, and these results can be used as guidelines for MCO performance measurement. The simulation findings also suggest that mortality, average monthly cost, and number of nursing-home-free years should be examined together when evaluating the quality of long-term care. This research suggests approach to constructing actual-to-expected quality indicators, along with simulated basis for determining what is unusual (good or bad) variation from expected.

7.2. Research significance

This research addresses the needs of many stakeholder groups: health care payers, health care purchasers, and health status modelers. As noted in the introduction to this dissertation, this research emphasis on finding factors that can predict future capitation levels. This research is a first study that aims in using a minimal number of factors to effectively predict future capitation rate among Medicaid managed LTC program recipients. Although there are other possible variables that can improve the prediction model, the identified variables are easy to assessed and accessed. So, the model from this dissertation can be applied in other states, and generate valid results.

For health care payers—the stakeholders that the Wisconsin state government represents—this research provides a first analysis of state-space modeling of capitation rate levels in the Wisconsin LTC program. The developed prediction model, along with the analytical and simulated projections, would be very helpful to health care payers in making any needed adjustments to budget and LTC setting planning, with the end goal of developing and identifying measures that better reflect LTC quality in MCOs. This research also suggests that different sizes of MCOs may use different measurements, and that there may be a tradeoff between mortality rate (or long life expectancy) and higher cost levels.

For health care purchasers such as patients or enrollees, this research provides initial information on possible future capitation levels based on current living situation. Additionally, this study provides information to LTC program enrollees for their possible future living arrangement. More informed expectations of future need for services facilitate personal planning. LTC enrollees can improve the assessment for future alternative care setting options and MCO selection.

Finally, for health care modelers who are working on modeling health status transitions, this research provides insights into new and adapted model structure and explanatory variables that can be used in developing health state-space modeling. In addition, this research reflects a first step toward providing a convenient and flexible methodology to handle sparse sample issues, and scientifically reducing the number of parameters in transition model.

7.3. Research Strength and Limitations

This research uses a rigorous methodology and incorporates data from state representative data sets. This research is one of the first analyses to identify the minimal number of factors that can explain capitation rate variations for individuals, and to propose simple parametric forms with the lowest possible number of estimations for transition rates. A major strength of this research is to demonstrate modeling procedures that makes several conventional methods are easier to be understood by general population. This research is one of the first studies to provide an appropriate grouping technique, creating a better and more deliverable explanation for SAS coefficient output.

Second, this research looks at not only statistical perspective but also takes available public U.S. life table results into account for which internal and external validities have been developed. An additional strength of this research is that the simulation results demonstrate that the analytical projection is useful for payers' budget planning activities. Finally, given that the status definition is based on capitation rate, these results can be easily reproduced in other states' managed LTC programs, because most state governments use this approach, paying monthly fix rate to MCO for each Medicaid LTC program enrollee, to manage Medicaid LTC program's finance.

One limitation of this research is that both the analytical and simulated projections are closed cohorts. Lack of information on new enrollees in each year could result in an average LTC cost for an MCO that is either too high or too low. Comprehensive modeling of LTC populations and service demand requires an additional prediction model to estimate annual new enrollees.

Another limitation is that this research withdraws lapses population while constructing the model. The characteristic of lapsed population are excluded while analyzing the transition rates. The results from this research may overestimate the expected cost among living population. The results would be more accurate if we could include the characteristics of lapsed population, but this approach would increase the difficulty of modeling the transition rate, because taking lapsed population into consideration requires additional analysis regarding to the reasons leading them to leave the program. The reasons of leaving the Medicaid program is usually driven by individual's financial situation that causes them disqualify Medicaid, and individual's financial qualification for Medicaid is affected by many reasons. Besides, individual may choose other private health insurance program for random reasons, thus including the lapsed population would require additional research for consumer's behaviors. The additional study for this population would be a beneficial extension of current work, but our model still provides fair estimation results.

This study does not model trends in the LTCS transition rates due to emerging technology or shifts in program policy. An understanding for the uncertainty of Wisconsin Family Care program is required. As any other Medicaid programs, the coverage of managed LTC program will change along with policy change, and so does Family Care program. The structure of enrollees may change over time due to not only policy but also new medical technologies or treatments, so the model structure would require adequate modification as well. For example, one new medical treatment is launched this year, and it is effective on dialysis patient. This treatment may significant prolong the expected life year among LTC population which could lead higher LTC cost for payers. Therefore, a lack of microsimulation model which incorporate with economics, policy, and other uncertain factors is a limitation of this study. .

7.4. Future Research Directions and Applications

This dissertation presents a completed research project. There are several directions that can be addressed in future research. First, from the policy improvement point of view, one of the most important avenues to pursue is the development of a dynamic forecasting model for the number of annual new and withdrawing Medicaid LTC program enrollees and the structure of their capitation rate. Public health care programs are in need of such a transition model to project future LTC demand and costs for an open cohort population. A model developed along these lines would allow incorporation of the closed cohort projections along with the population structure for new and withdrawing enrollees.

Second, a study should be performed to further investigate which factors causing the differences between expected and actual LTC cost. For example, bird flu offsets in certain area, so the mortality in nearby MCO is higher compared to expected mortality. This is an important avenue to pursue in order to understand the latent risk factors for actual LTC cost. In addition, the magnitude of modeling noise due to medial events should be investigated in the future.

Third, a different methodology of identifying neighbor populations for grouping purposes should be investigated. There are five dimensions that can be pursued in order to understand which combinations of independent variables share the same distribution for both living situations and capitation rate levels. In this study, I groups sample by their living situation if the sample is sparse; however, other independent variable such as age, gender and current LTCS are possible other directions that can be grouped. Full investigation for all dimensions can provide a more dynamic approach of grouping sparse samples with appropriate neighbors, and this future direction can improve the developed prediction model.

Finally, a further statistical analysis of the internal validity should be performed. Although this study did not test the internal validity of the developed model from validation data globally, the validity of the constructed model has been proven by a sequence of tests locally. However, a study investigating the relationship between actual transition rates from validation data and expected transition rates estimated by the developed model globally by overall chi-square test may be beneficial.

This dissertation can be applied in several areas: LTC financing and facilities planning, quality measurement and award systems development, decision-making tools, and health economic outcome research. Discussions of these areas are presented below.

From the payer's perspective, this research can be expanded to analyze other managed LTC program in other states. The transition matrixes can be used for analytical projections, and the results can provide important guidance for state and federal government budget planning. Many studies have pointed out that well-planned LTC financing and facilities improve the quality of healthcare delivery systems.[82–85] Therefore, this model is a useful tool to enhance payers' forecasting ability. Further, the model results can be generalized across the entire United States, and thus the federal government can apply the estimations for policy recommendations.

An understanding of quality of care is essential, and a need for comprehensive measurement has been repeatedly discussed in the literature.[86] A study should be performed to further compare the expected and actual transition rates for all individuals within each MCO and between MCOs derived from the developed model. This is an important avenue to pursue in order to standardize and generalize MCO quality measurement practices. In addition, the variation of expected results within each MCO and between MCOs should be investigated in the future. Urban and rural factors should also be taken into account in future research. The findings could eventually be translated into a standard award system. For example, the ratio of monthly average cost over mortality rate can be used as an essential indicator. The bigger number is, the better quality of care provided by MCO.

Finally, the structure of state-based modeling techniques developed in this research can be applied to health economic outcome research (HEOR) in the future. The base rate model is useful for intervention studies. For example, this model is a very useful tool to help drug developers and manufacturers decide whether to invest further in a specific drug. The usage of the drug can be tested as one of the independent variables. If the drug shows a significant impact on individual status transition rates, this result supports an argument that the drug is effective. The model can estimate the expected transition rates for both drug research and control groups and then compare the actual and expected transition rates for both groups. The difference between expected and actual transition rates for both groups provides insight for health outcome researchers. Similarly, outcome research can measure the performance of medical technologies.

7.5. Conclusion

In summary, this dissertation research has provided an important contribution to the area of LTC state-space modeling. It identifies the minimal number of factors that can be used to model transition rates for individuals, develops status transition rate matrixes, yields flexible and simple parametric forms, conducts analytical and simulated projections, and outlines future research directions and possible applications. This is one of the first dissertations to bridge the gap between the statistical model construction perspective and the industrial and system engineering perspective, and the synthesized research findings greatly contribute to the health system engineering area.

Reference

1. Grayson V, Victoria Velkoff. The next four decades, the older population in the united states: 2010 to 2050. Washington, DC: U.S. Census Bureau; 2010:p25–1138.

2. Anderson WL, Armour BS, Finkelstein EA, Wiener JM. Estimates of state-level health-care expenditures associated with disability. *Public Health Rep*. 2010;125(1):44–51.

3. Anderson WL, Wiener JM, Finkelstein EA, Armour BS. Estimates of national health care expenditures associated with disability. *Journal of Disability Policy Studies*. 2011;21(4):230 – 240. doi:10.1177/1044207310391407.

4. Knickman JR, Snell EK. The 2030 problem: caring for aging baby boomers. *Health Services Research*. 2002;37(4):849–884.

5. Martin LG, Schoeni RF, Andreski PM. Trends in health of older adults in the united states: past, present, future. *Demography*. 2010;47(S):S17–S40.

6. Guralnik JM, Alecxih L, Branch LG, et al. Medical and long-term care costs when older persons become more dependent. *Am J Public Health*. 2002;92(8):1244–1245.

7. Manton KG, Stallard E, Singer BH. *Methods for projecting the future size and health status of the US elderly population*. University of Chicago Press; 1994.

8. Stallard E. Estimates of the incidence, prevalence, duration, intensity, and cost of chronic disability among the US elderly. *North American Actuarial Journal*. 2011;15:32–58.

9. Manton KG, Gu X, Lamb VL. Change in chronic disability from 1982 to 2004/2005 as measured by long-term changes in function and health in the U.S. elderly population. *Proceedings of the National Academy of Sciences*. 2006;103(48):18374 –18379. doi:10.1073/pnas.0608483103.

10. Soldo BJ, Manton KG. Changes in the health status and service needs of the oldest old: current patterns and future trends. *The Milbank Memorial Fund Quarterly. Health and Society*. 1985;63(2):286–319.

11. Favreault M, Smith K. A primer on the dynamic simulation of income model (DYNASIM3). Urban Institute. 2004.

12. Kneell D, Alecxih L, Wiener JM, Hanley RJ. Brookings/ICF Long-Term Care Financing Model: Model Assumption. Brookings/ICF. 1992

13. Goldman DP. *Health status and medical treatment of the future elderly: Final Report*. Rand Corporation; 2004.

14. Wunderlich GS. Improving Health Care Cost Projections for the Medicare Population: Summary of a Workshop. Natl Academy Pr; 2010.

15. De Leon CF., Glass TA, Beckett LA, Seeman TE, Evans DA, Berkman LF. Social networks and disability transitions across eight intervals of yearly data in the New Haven EPESE. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*. 1999;54(3):S162.

16. Hardy SE, Dubin JA, Holford TR, et al. Transitions between states of disability and independence among older persons. *American Journal of Epidemiology*. 2005;161(6):575 –584. doi:10.1093/aje/kwi083.

17. Shi L, Singh DA. *Delivering health care in America: A systems approach*. Jones & Bartlett Learning; 2008.

18. Robinson J. A long-term care status transition model. *The Old-Age Crisis: Actuarial Opportunities*. 1996.

19. Meyerson N, Schwabish C, Simpson M, et al. *CBO's Long-Term Model: An Overview*.; 2009.

20. Congressional Budget Office. Available at: http://www.cbo.gov/. Accessed April 13, 2011.

21. Johnson RJ, Wolinsky FD. The structure of health status among older adults: disease, disability, functional limitation, and perceived health. *Journal of Health and Social Behavior*. 1993;34(2):105–121.

22. Topoleski J, Manchester J. Modeling Health Status and Health Transitions in Microsimulation Models. Congressional Budget Office; 2009.

23. Feder J, Komisar HL, Niefeld M. Long-term care in the United States: An overview. *Health Affairs*. 2000;19(3):40.

24. Keehan S, Sisko A, Truffer C, et al. Health spending projections through 2017: the baby-boom generation is coming to Medicare. *Health Affairs*. 2008;27(2):w145.

25. Truffer CJ, Keehan S, Smith S, et al. Health spending projections through 2019: the recession's impact continues. *Health Affairs*. 2010;29(3):522.

26. Chollet DJ. *Microsimulation models in health services research*. 1990.

27. Favreault MM, Sammartino FJ, Steuerle CE. Social security benefits for spouses and survivors. *Social Security and the family: Addressing unmet needs in an underfunded system*. 2002:177.

28. Zedlewski SR, McBride TD. The changing profile of the elderly: effects on future long-term care needs and financing. *The Milbank Quarterly*. 1992;70(2):247–275.

29. Favreault M, Mermin G, Steuerle CE. Minimum Benefits in Social Security. 2006.

30. Mermin G. Would raising the social security retirement age harm low-income groups? 2006.

31. Butrica B, Toder E, Toohey D. *Boomers at the bottom: how will low income boomers cope with retirement.*; 2008.

32. Butrica B, Uccello C. *How will boomers fare at retirement?* 2004.

33. Johnson RW. Meeting the long-term care needs of the baby boomers: how changing families will affect paid helpers and institutions. 2007.

34. Hanley RJ, Alecxih LM, Wiener JM, et al. Predicting elderly nursing home admissions. results from the 1982-1984 national long-term care survey. *Research on aging*. 1990;12(2):199.

35. Kemper P, Komisar HL, Alecxih L. Long-term care over an uncertain future: what can current retirees expect? *Inquiry*. 2005;42(4):335–350.

36. Kronick R, Rousseau D. Is Medicaid Sustainable? spending projections for the program's second forty years. *Health Affairs*. 2007.

37. Wiener JM, Rubin RM. The potential impact of private long-term care financing options on Medicaid: the next thirty years. *Journal of health politics, policy and law*. 1989;14(2):327.

38. Knickman JR, Hunt KA, Snell EK, et al. Wealth patterns among elderly Americans: implications for health care affordability. *Health Affairs*. 2003;22(3):168 –174. doi:10.1377/hlthaff.22.3.168.

39. The future elderly model, Developed by the RAND Roybal Center for Health Policy Simulation | RAND. http://www.rand.org/labor/roybalhp/about/fem.html. Accessed April 28, 2011.

40. Centers for Medicare & Medicaid Services. NHE Fact Sheet. https://www.cms.gov/NationalHealthExpendData/25_NHE_Fact_Sheet.asp#TopOfPage. Accessed April 25, 2011.

41. Goldman DP. *Health status and medical treatment of the future elderly: Final Report*. Rand Corporation; 2004.

42. Chernew ME, Goldman DP, Pan F, et al. Disability and health care spending among Medicare beneficiaries. *Health Affairs*. 2005.

43. Joyce GF, Keeler EB, Shang B, et al. The lifetime burden of chronic disease among the elderly. *Health Affairs*. 2005.

44. Cutler DM. The potential for cost savings in Medicare's future. *Health Affairs*. 2005.

45. Lakdawalla DN, Goldman DP, Shang B. The health and cost consequences of obesity among the future elderly. *Health Affairs*. 2005.

46. Headquarters C. Modeling the Health and Medical Care Spending of the Future Elderly. 2008.

47. Bhandari A, Wagner T. Self-reported utilization of health care services: improving measurement and accuracy. *Medical Care Research and Review*. 2006;63(2):217–235.

48. Ritter PL, Stewart AL, Kaymaz H, et al. Self-reports of health care utilization compared to provider records. *Journal of clinical epidemiology*. 2001;54(2):136–141.

49. Longobardi T, Walker JR, Graff LA, et al. Health service utilization in IBD: comparison of self-report and administrative data. *BMC health services research*. 2011;11(1):137.

50. MacDonald D, Murray M, Collins KD, et al. Challenges and opportunities for using administrative data to explore changes in health status: a study of the closure of the new found land cod fishery. *Population health management*. 2009;12(6):345–352.

51. Roos LL, Gupta S, Soodeen RA, et al. Data quality in an information-rich environment: Canada as an example. *Canadian Journal on Aging/La Revue canadienne du vieillissement*. 2005;24(S1):153–170.

52. Sibley LM, Moineddin R, Agha MM, et al. Risk adjustment using administrative data-based and survey-derived methods for explaining physician utilization. *Medical care*. 2010;48(2):175.

53. Singh JA. Discordance between self-report of physician diagnosis and administrative database diagnosis of arthritis and its predictors. *The Journal of rheumatology*. 2009;36(9):2000–2008.

54. PricewaterhouseCoopers. *Calendar Year 2011 Family Care Capitation Rates*.; 2011.

55. Wisconsin Department of Health Service. http://www.dhs.wisconsin.gov/LTCare/Generalinfo/WhatisFC.htm. Accessed April 19, 2011.

56. Anderson RT, James MK, Miller ME, et al. The timing of change: patterns in transitions in functional status among elderly persons. *The Journals of Gerontology: Series B*. 1998;53(1):S17.

57. Crimmins EM, Saito Y. Getting better and getting worse. *Journal of Aging and Health*. 1993;5(1):3.

58. Manton KG, Soldo BJ. Disability and mortality among the oldest old: Implications for current and future health and long-term-care service needs. *The oldest old*. 1992:199–250.

59. Verbrugge LM. Disability transitions for older persons with arthritis. *Journal of Aging and Health*. 1992;4(2):212.

60. Manton KG. A longitudinal study of functional change and mortality in the United States. *Journal of Gerontology*. 1988;43(5):S153 –S161. doi:10.1093/geronj/43.5.S153.

61. Branch LG, Katz S, Kniepmann K, et al. A prospective study of functional status among community elders. *American Journal of Public Health*. 1984;74(3):266.

62. Beckett LA, Brock DB, Lemke JH, et al. Analysis of change in self-reported physical function among older persons in four population studies. *American Journal of Epidemiology*. 1996;143(8):766.

63. Manton KG, Corder LS, Stallard E. Estimates of change in chronic disability and institutional incidence and prevalence rates in the US elderly population from the 1982, 1984, and 1989 National Long Term Care Survey. *Journal of Gerontology*. 1993;48(4):S153.

64. Gillen P, Spore D, Mor V, et al. Functional and residential status transitions among nursing home residents. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*. 1996;51(1):M29.

65. Rosenstein RB, Spector WD, Freiberger WF. Transition probabilities for functional change and discharge status of nursing home patients. *American Statistical Association Proceedings of the Social Statistical Section, New Orleans, LA*. 1988.

66. Multinomial logistic regression. *Wikipedia, the free encyclopedia*. 2013. http://en.wikipedia.org/w/index.php?title=Multinomial_logistic_regression&oldid=547881056. Accessed April 9, 2013.

67. Allison PD. *Logistic Regression Using SAS: Theory and Application*. SAS Institute; 2012.

68. Lawal B, Lawal HB. *Categorical Data Analysis With Sas and Spss Applications*. Psychology Press; 2012.

69. Engelhardt GV, Greenhalgh-Stanley N. Home health care and the housing and living arrangements of the elderly. *Journal of Urban Economics*. 2010;67(2):226–238.

70. Martikainen P, Moustgaard H, Murphy M, et al. Gender, living arrangements, and social circumstances as determinants of entry into and exit from long-term institutional care at older ages: a 6-year follow-up study of older Finns. *The Gerontologist*. 2009;49(1):34–45.

71. Cai L, Schenker N, Lubitz J. Analysis of functional status transitions by using a semi-Markov process model in the presence of left-censored spells. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*. 2006;55(4):477–491.

72. Lehnert T, Sonntag D, Konnopka A, Riedel-Heller S, König H-H. The long-term cost-effectiveness of obesity prevention interventions: systematic literature review. *obesity reviews*. 2012;13(6):537–553.

73. OACT. Life Tables. http://www.ssa.gov/oact/NOTES/as120/LifeTables_Body.html. Accessed March 22, 2013.

74. Hogg RV, Craig AT. *Introduction to mathematical statistics*. 4th ed.; 1978.

75. McGlynn EA. Six challenges in measuring the quality of health care. *Health Affairs*. 1997;16(3):7–21.

76. Mainous 3rd AG, Talbert J. Assessing quality of care via HEDIS 3.0. Is there a better way? *Archives of family medicine*. 1998;7(5):410.

77. Neumann PJ, Levine B-S. Do HEDIS measures reflect cost-effective practices? *American Journal of Preventive Medicine*. 2002;23(4):276–289.

78. Berger WE, Legorreta AP, Blaiss MS, et al. The utility of the Health Plan Employer Data and Information Set (HEDIS) asthma measure to predict asthma-related outcomes. *Annals of Allergy Asthma and Immunology*. 2004;93(6):538–545.

79. Lim KG, Patel AM, Naessens JM, et al. Flunking Asthma? When HEDIS Takes the ACT-Page. *Am J Manag Care*. 2008;14(8):487–494.

80. Cella DF, Tulsky DS. Measuring quality of life today: methodological aspects. *Oncology (Williston Park, NY)*. 1990;4(5):29.

81. Agresti A, Liu I. Strategies for Modeling a categorical variable allowing multiple category choices. *Sociological Methods & Research*. 2001;29(4):403–434. doi:10.1177/0049124101029004001.

82. Chung R, Tin K, Cowling B, et al. Long-term care cost drivers and expenditure projection to 2036 in Hong Kong. *BMC Health Services Research*. 2009;9(1):172.

83. Elliott MN. Using indirect estimation using indirect estimation to improve CMS administrative information on race/ethnicity and estimate plan level HEDIS and estimate plan-level hedis performance by race/ethnicity. 2010.

84. Epstein AM. Medicaid managed care and high quality: can we have both? *JAMA*. 1997;278(19):1617–1621. doi:10.1001/jama.1997.03550190085052.

85. Lee R, Miller T. An approach to forecasting health expenditures, with application to the US Medicare system. *Health Services Research*. 2002;37(5):1365–1386.

86. Landon BE, Schneider EC, Normand S-LT, et al. Quality of care in Medicaid managed care and commercial health plans. *JAMA*. 2007;298(14):1674–1681. doi:10.1001/jama.298.14.1674.

Appendix A: Piecewise Liner Function *for Age*

Each starting status which combines LTCS and living situation has three different transition matrixes by age levels and gender. The age levels are: 60-72, 73-85, 85+. Instead of setting the transition matrixes consistent in the age range, piecewise liner function is applied to make appropriate adjustments. The details of each step are explained below.

1. The age 67, 79, and 91 are set as the middle points in age level 60-72, 73-85, and 85+, respectively. The fitted transition matrixes by starting status and gender are assigned mode from developed model to these ages.
2. β_1 is the minimal value while comparing the difference between age 67 transition matrix and age 79 transition matrix. B_2 is the minimal value while comparing the difference between age 79 transition matrix and age 91 transition matrix. If the difference is bigger than 1, the β is 1.
3. The equations of P_{ij}^{age} are presented below:

$$\begin{cases} P_{ij}^{67} - \frac{\beta_1^i \times \left(P_{ij}^{79} - P_{ij}^{67}\right)}{(79-67)} \times (67 - age)\ as\ age\ is\ from\ 60\ to\ 66 \\ P_{ij}^{67} + \frac{\left(P_{ij}^{79} - P_{ij}^{67}\right)}{(79-67)} \times (age - 67)\ as\ age\ is\ from\ 67\ to\ 78 \\ P_{ij}^{79} + \frac{\left(P_{ij}^{91} - P_{ij}^{79}\right)}{(91-79)} \times (age - 79)\ as\ age\ is\ from\ 79\ to\ 90 \\ P_{ij}^{91} + \frac{\beta_2^i \times \left(P_{ij}^{91} - P_{ij}^{79}\right)}{(91-79)} \times (age - 91)\ as\ age\ is\ from\ 91\ to\ 100 \end{cases}$$

Appendix B: *Chi*-squared value and *p*-value distribution for Model Construction Dataset versus Validation Dataset

Chi-square tests for dataset consistency

i	Starting LTCS	Gender	Age	Living Situation	Q	p-value
1	A	F	A	HA	10.83	0.05
2	A	F	A	H	2.00	0.85
3	A	F	A	C	4.07	0.54
4	A	F	A	I	3.00	0.39
5	A	F	B	HA	11.53	0.04
6	A	F	B	H	6.77	0.24
7	A	F	B	C	3.87	0.42
8	A	F	B	I	5.96	0.31
9	A	F	C	HA	3.51	0.62
10	A	F	C	H	4.33	0.50
11	A	F	C	C	7.07	0.22
12	A	F	C	I	1.88	0.39
13	A	M	A	HA	3.19	0.67
14	A	M	A	H	8.99	0.11
15	A	M	A	C	4.44	0.35
16	A	M	A	I	1.58	0.67
17	A	M	B	HA	7.40	0.19
18	A	M	B	H	7.74	0.17
19	A	M	B	C	2.26	0.52
20	A	M	B	I	3.00	0.22
21	A	M	C	HA	6.20	0.29
22	A	M	C	H	5.85	0.21
23	A	M	C	C	6.16	0.10
24	A	M	C	I	0.00	NA
25	B	F	A	HA	3.91	0.56
26	B	F	A	H	5.74	0.33
27	B	F	A	C	3.85	0.57
28	B	F	A	I	9.17	0.06
29	B	F	B	HA	4.89	0.43
30	B	F	B	H	3.08	0.69
31	B	F	B	C	8.88	0.11
32	B	F	B	I	3.55	0.62
33	B	F	C	HA	0.41	1.00
34	B	F	C	H	3.51	0.62
35	B	F	C	C	3.03	0.70
36	B	F	C	I	4.71	0.32

37	B	M	A	HA	9.99	0.08
38	B	M	A	H	11.14	0.05
39	B	M	A	C	4.13	0.53
40	B	M	A	I	4.98	0.42
41	B	M	B	HA	0.82	0.98
42	B	M	B	H	4.65	0.46
43	B	M	B	C	4.37	0.50
44	B	M	B	I	3.15	0.53
45	B	M	C	HA	2.94	0.71
46	B	M	C	H	9.36	0.10
47	B	M	C	C	3.93	0.56
48	B	M	C	I	3.75	0.29
49	C	F	A	HA	10.97	0.05
50	C	F	A	H	4.74	0.45
51	C	F	A	C	8.49	0.13
52	C	F	A	I	2.50	0.78
53	C	F	B	HA	5.04	0.41
54	C	F	B	H	10.48	0.06
55	C	F	B	C	9.56	0.09
56	C	F	B	I	4.89	0.43
57	C	F	C	HA	1.56	0.91
58	C	F	C	H	11.22	0.02
59	C	F	C	C	21.56	0.00
60	C	F	C	I	7.04	0.22
61	C	M	A	HA	7.74	0.17
62	C	M	A	H	7.72	0.17
63	C	M	A	C	8.60	0.13
64	C	M	A	I	4.07	0.54
65	C	M	B	HA	4.26	0.51
66	C	M	B	H	1.21	0.94
67	C	M	B	C	6.40	0.17
68	C	M	B	I	3.70	0.45
69	C	M	C	HA	2.37	0.80
70	C	M	C	H	3.21	0.52
71	C	M	C	C	13.45	0.01
72	C	M	C	I	2.06	0.56
73	D	F	A	HA	15.01	0.01
74	D	F	A	H	8.90	0.11
75	D	F	A	C	5.28	0.26
76	D	F	A	I	4.79	0.44
77	D	F	B	HA	10.97	0.05
78	D	F	B	H	2.42	0.79

79	D	F	B	C	5.23	0.39
80	D	F	B	I	4.66	0.46
81	D	F	C	HA	6.21	0.29
82	D	F	C	H	10.81	0.03
83	D	F	C	C	1.51	0.82
84	D	F	C	I	5.48	0.36
85	D	M	A	HA	3.59	0.46
86	D	M	A	H	17.91	0.00
87	D	M	A	C	5.45	0.36
88	D	M	A	I	4.11	0.53
89	D	M	B	HA	8.12	0.09
90	D	M	B	H	5.83	0.32
91	D	M	B	C	10.16	0.07
92	D	M	B	I	2.24	0.69
93	D	M	C	HA	3.13	0.37
94	D	M	C	H	4.07	0.40
95	D	M	C	C	1.17	0.88
96	D	M	C	I	4.79	0.31
97	E	F	A	HA	4.06	0.54
98	E	F	A	H	4.19	0.52
99	E	F	A	C	6.33	0.18
100	E	F	A	I	2.13	0.71
101	E	F	B	HA	1.33	0.86
102	E	F	B	H	3.92	0.42
103	E	F	B	C	3.22	0.52
104	E	F	B	I	4.36	0.50
105	E	F	C	HA	6.31	0.18
106	E	F	C	H	3.36	0.34
107	E	F	C	C	4.58	0.33
108	E	F	C	I	1.75	0.88
109	E	M	A	HA	6.79	0.15
110	E	M	A	H	10.48	0.03
111	E	M	A	C	3.27	0.35
112	E	M	A	I	12.89	0.01
113	E	M	B	HA	1.89	0.39
114	E	M	B	H	6.51	0.16
115	E	M	B	C	1.98	0.58
116	E	M	B	I	2.70	0.61
117	E	M	C	HA	2.00	0.37
118	E	M	C	H	1.44	0.70
119	E	M	C	C	0.07	0.96
120	E	M	C	I	3.23	0.52