Minnesota Long-Term Services and Support Projection Model

Conceptual Model

May 11, 2018

Prepared for:

LaRahe Knatterud
Director, Aging Transformation
Minnesota Department Human Services

Prepared by:

Lynn A. Blewett, PhD[1]
Giovann Alarcon Espinoza, MPP[1]
Robert Hest, MPP[1]
Mark Woodhouse, BA[2]

Affiliations:

1. State Health Access Data Assistance Center (SHADAC), Division of Health Policy and Management, University of Minnesota, School of Public Health
2. Division of Health Policy and Management, University of Minnesota, School of Public Health

TABLE OF CONTENTS

BACKGROUND

The University of Minnesota's State Health Access Data Assistance Center (SHADAC), in collaboration with the Minnesota Department of Human Services, has developed a LTSS projection model to assist the state with planning for the continued growth in the elderly population. The number of older adults (age 65 and older) in the U.S. is expected to more than double in the next 40 years, and it is estimated that 70 percent of older adults will use some type of LTSS during their lifetime. The oldest of the elderly (age 85 and over) are the fastest-growing age group in the U.S. and are over four times more likely to need LTSS than the elderly between the ages of 65 and 84 (HHS 2016).

Minnesota demographic trends follow a similar pattern. By 2020 the Minnesota Demographic Center estimates that Minnesotans age 65+ will grow by nearly 20 percent, resulting in an additional 160,000 older adults. By 2030, the total number of older adults in the state will grow to 1.28 million. While older adults account for about 16 percent of the state's population, by 2030 they will make up 22 percent of the population — that is, one out of every five Minnesotans will be age 65 or older (MN Demographic Center 2018). And due to Minnesota's long life expectancy of 81 years, Minnesota's population age 85 and older is expected to grow from 2.2% in 2015 to 5.8% in 2050 (AARP 2015).

LTSS encompasses the broad range of paid and unpaid medical and personal care assistance that people may need, for several weeks, months, or years, when they experience difficulty completing self-care tasks (Kaiser Family Foundation 2015). LTSS services, both in institutional settings and in the community, are also expensive; an estimated $310 billion was spent on LTSS in 2013 alone (Kaiser Family Foundation 2015). The majority of LTSS is paid for by Medicaid, at a tremendous and growing expense to the state. We have developed a tool for the state of Minnesota to assist in the planning for the future impact of these demographic trends both for the needs of individuals but also for impact on state programs and services, particularly state Medicaid financing.

Using Minnesota-specific data and based on assumptions that reflect Minnesota's trends and policy environment, SHADAC has developed a population and cost projection model. Using 2015 as the base year, this model projects the population in Minnesota, their characteristics, their use of LTSS, and state spending on these services into 2020 and 2030.

Model Overview

We developed a Minnesota-specific LTSS projection model using state-specific data and the projection of demographic changes over time. Our model projects the use and costs of LTSS for MN's Medicaid elderly population, estimates potential future costs of Medicaid based on current use, and allows for estimating impact on costs of key policy interventions. As such, we exclude from our analysis acute services received by the elderly and LTSS received by disabled individuals under the age of 65.

We used 2015 baseline data on Minnesota residents from the American Community Survey (ACS) and data on state Medicaid expenditures on LTSS from Minnesota's Medicaid Management Information System (MMIS). Other data sources used in the model include the national Health and Retirement Study and the Survey of Older Minnesotans.

The model development included the following key steps:

1. **Cohorts:** we defined a set of 96 cohorts based on determinant variables that are important predictors of LTSS use/cost, as well as variables that are determinants of enrollment in Long-term Care Insurance programs and policies, as suggested by previous research. These cohorts are not the unit of analysis, but allow us to precisely link our model's utilization projections with average cost data from the MMIS to produce projections of total cost.
2. **Cost Baseline, Current Users:** we established a baseline for the model using data from the MMIS to estimate the distribution of current users of LTSS and total Medicaid costs across the cohorts.
3. **Future Users:** we identified the population that will potentially use LTSS in the period of analysis (2015-2030) and estimated the distribution of potential users across the cohorts using data from the ACS, specific to Minnesota residents.
4. **Demographic Projections:** we estimated demographic changes in the potential future LTSS user population to 2020 and 2030.
5. **Eligibility Scenarios:** we modeled Minnesotans' eligibility for Medicaid using three scenarios: high, medium, and low rates of eligibility among the elderly population.
6. **Policy Impacts:** we estimated the policy impact on eligible individuals' LTSS utilization based on number and average and total costs of Medicaid users of LTSS. The first policies being assessed include an embedded Enhanced Home Care Benefit in Medicare Supplemental Health Insurance policies and a new hybrid long-term care/life insurance policy, LifeStage.
7. **Cost Projection:** we linked the average cost of LTSS to each cohort by type of service in the projected years. We apply an estimated inflation rate to these data for the purposes of making fiscal projections, but the data are also available in 2015 dollars in order to facilitate comparisons with the baseline.

An important limitation of our model is that it uses a partial equilibrium framework. The model uses information on how the population changes through time and how polices affect the cohorts and costs, but it cannot look further into how individual effects also might affect one another simultaneously (e.g., how a policy impact might also affect the demographic changes of the population or how changes in utilization patterns impact the prices or supply of health care services).

Cohorts Definition

The first step in our model was to define the specific characteristics that characterize the different groups of individuals and will help us link our cost estimations with the model's utilization estimates. To define these cohorts, we used five determinant variables: age, sex, Medicaid eligibility, urbanicity, limitations to Activities of Daily Living (ADLs), and type of LTSS. These variables were selected using two criteria: (i) they are important predictors of LTSS use/cost, or (ii) they are used to define eligibility to potential Long-Term Care insurance (or LTSS-related) programs and policies in Minnesota.

Based on evidence about the relationship between these variables and the use and cost of LTSS, we defined a set of categories for each determinant variable:

1. **Age Groups:** 50-54, 55-59, 60-64 65-74, 75-84, and 85+.
2. **Sex:** male and female.
3. **Medicaid eligibility:** eligible and not eligible.
4. **Urbanicity:** urban and rural.
5. **Activities of Daily Living (inability to perform):** 0-1 and 2+.
6. **Type of LTSS:** home and community based services or services provided at a nursing facility

The scope of our analysis makes us ignore some of these categories in any final report. In particular, we include individuals aged 50-54 at the baseline because they would be 65 or over by 2030, but we do not include in our utilization estimates anyone who is not 65 or older at the time of analysis. Similarly, we focus on the population who is eligible for Medicaid, and ignore those who are not eligible. Thus, based on every unique combination among the different categories of each determinant variable, we established 96 cohorts.

The potential future LTSS user population is distributed along these 96 cohorts using data from the 2015 five-year ACS to establish the extended baseline (this extended baseline does not include average cost because it includes people who do not currently use LTSS). Based on this distribution, the model uses the information on policy impacts and combines it with the estimated demographic changes to project a new distribution of LTSS users in 2020 and 2030.

The model uses current information about the current cohort of individuals (e.g., age and race) as well as other relevant characteristics (e.g., marital status, homeownership, availability of caregivers in the family) to predict the cohort in which they will be in 2020 and 2030. Although this allows for the possibility of having transitions in time between almost each cohort to every other cohort, individuals have a limited number of cohorts to which they may transition in the future. This is because, for example, once someone gains an ADL, they are highly likely to have it in the future, and that limits the number of cohorts to which they can go (as other cohorts are excluded due to not being consistent with the specific characteristics at baseline for the individual).

Finally, we made two exclusions to our data when projecting this population into 2020 and 2030 (see Section four for more details on these exclusions). These projections allowed us to change our analysis from the potential future LTSS users (i.e., all Minnesotans aged 50 or over) to the projected LTSS users (i.e., all Minnesotans 65 or over who are eligible for Medicaid and require LTSS).

BASELINE DATA

Before doing any projections, we first created a baseline. Our baseline consists of two datasets, one focused on current Medicaid LTSS costs and utilization and one focused on the pool of potential future users of LTSS. The cost baseline gives us a point of comparison for our 2020 and 2030 LTSS cost and utilization projections, while the future LTSS users baseline gives us a current representative sample of Minnesotans that the model uses to project into 2020 and 2030.

To consider which services we included in our estimates, we followed Kaiser's definition of LTSS: "broad range of paid … medical and personal care assistance that people may need — for several weeks, months, or years — when they experience difficulty completing self-care tasks" (Kaiser Family Foundation 2015).

In this section, we first explain how we created our cost baseline of current Medicaid LTSS users, describing our definitions of utilization and cost and how we capped certain costs to avoid the influence of outlier cases. Second, we show how we created our baseline of potential future LTSS users, which we present in 96 cohorts as described in the previous section. We describe the data sources and variables we used to construct this baseline of future LTSS users.

Current LTSS Users

We constructed a baseline of cost data for users of Medicaid LTSS in our base year, 2015, using claims and encounter data from Minnesota's Medicaid Management Information System (MMIS). These data were used to define Medicaid LTSS utilization and costs for a total of 96 cohorts and form the basis of our cost projections for 2020 and 2030. We limited costs to those costs associated with LTSS for Medicaid enrollees age 65 and older. We excluded costs associated with other services paid by Medicaid (e.g. acute care), paid by other programs (e.g., Medicare, and the Alternative Care, and Essential Community Supports programs) or for other populations (e.g., non-elderly disabled).

As explained in the previous section, the data were categorized into 96 cohorts defined by Age (65-74, 75-84, 85+), Sex (Female/Male), Urbanicity (Rural/Urban), Race/ethnicity (White/Nonwhite), ADL status (<2 ADL limitations, 2+ ADL limitations), and by type of LTSS service (HCBS and NF). We imputed ADLs for individuals with missing ADL information using a hot-deck routine. Our definition of a Nursing Facility (NF) resident is someone who has: i) stayed 100 or more consecutive days at a nursing facility (this may include partial stays in 2014 or 2016), ii) had a at least one nursing facility stay in 6 or more months in 2015, or ii) spent 180 or more days in a nursing facility in 2015.

Each cohort has an associated number of users, total annual LTSS cost, and per capita average annual cost. These cohorts and cost figures allowed us to produce 2020 and 2030 total cost estimates by matching our baseline of average cost by cohort with estimates by cohort of future LTSS users eligible for Medicaid.

In order to reduce the potential bias of our LTSS cost data, we implemented to adjustments to the observed data. The first was substituting capitation claims with an estimated cost of the original service. The second was capping outlier services.

Capitation Claims

Capition claims constituted forty-six percent of all Medicaid spending in 2015. However, they do not represent the real cost of the service provided, which we need for our projections. Thus, we disaggregated all claims under the capitation category into the service that was provided and assigned in their stead the regular costs of the services provided under these claims. Since the purpose of estimating this baseline is to project costs into 2020 and 2030 based on the use of LTSS, the model uses these disaggregated costs as they better reflect these utilization patterns.

Cost Caps

Though we included all valid claims in our analysis, we addressed the potential bias produced by outlier cost claims by establishing cost caps. We capped costs on a monthly and per-service basis so that our caps could be applied at a more granular level to control the influence of true outlier services provided to Medicaid enrollees while retaining meaningful variation in our baseline. See Table 1 for a full list of categories and caps.

We capped costs differently based on three types of service categories: (i) rare services, (ii) cost drivers, and (iii) other services. Rare services were defined as service categories appearing with a non-zero cost (or estimated cost for PHP encounter claims) in less than one percent of all eligible person-months. Cost drivers were defined as service categories accounting for at least two percent of total annual Medicaid costs within our cost baseline. Other services were defined as service categories that were neither rare services nor cost drivers.

Cost caps were applied using the following rules:

1. Costs were aggregated on a person-month-category basis; Median, 99th Percentile, and Max values were identified.
2. The size (number of person-months) and range (99th Percentile-Max claim) of the 99th percentile of person-month-category costs were derived for each category. We refer to this as the “overhead” range.
3. Distributions of person-month costs were analyzed within the top one percent to determine where discontinuities in the distribution begin. The point where an identifiable discontinuity occurs is a likely place to set a cap in order to reduce the influence of outlier person-months on cost projections.
4. We then experimented with different intervals to group monthly costs within the overhead, searching for clear patterns in the distribution. Where we could find a pattern, we typically imposed a cap for that service.
5. We applied different assumptions to Rare Services and Cost Drivers.
    a. For rare services, we preferred not to impose any cap unless there was very strong evidence of a discontinuity, since each case that is capped destroys more information when there are few person-months in the overhead.
    b. For cost driver services, we again preferred not to impose any cap without very strong evidence of a discontinuity, since these services are more important to the overall cost picture. However, in general we were more aggressive with cost driver services than we were in the case of rare services.
    c. For other services, we imposed caps where there seemed to be a relatively sharp decline in frequencies. Our rule of thumb was two intervals with successive drops of fifty percent in the number of cases.
6. Our general goal was to cap as few person-months as practical while still reining in the true outliers.

Table 1. Services and Cost Caps

Service	Service Category	Median Cost ($)	99th Percentile Cost ($)	Max Cost ($)	Cap ($)	Capped person-months
Durable Medical Equipment & Supplies (Non-LTSS-Specific)	Cost Driver	81	1,268	38,065	3,300	592
Hospice Care	Cost Driver	3,970	7,771	14,510	9,400	19
ICF/MR	Cost Driver; Rare Service	6,348	11,960	16,578	No cap	0
Intellectual Disability Services	Cost Driver	4,981	12,743	25,687	15,500	24
Inpatient Hospital	Cost Driver	1,768	36,562	177,229	No cap	0
LTSS: Adult Foster Care	Cost Driver	6,074	17,448	31,246	No cap	0
LTSS: Customized Living	Cost Driver	1,959	7,694	15,314	No cap	0
LTSS: Nursing Facility	Cost Driver	4,329	8,590	45,468	No cap	0
LTSS: Personal Care	Cost Driver	1,997	6,140	21,751	13,000	12
Outpatient Medical Services	Cost Driver	126	2,896	64,061	8,000	437
Adult Day Care	Rare Service	809	2,026	2,591	No cap	0
Assisted Living (Non-LTSS)	Rare Service	3,874	14,479	14,479	No cap	0
Home Health Services (Non-LTSS)	Rare Service	78	697	2,380	No cap	0
LTSS: Adult Day Services	Rare Service	739	1,985	2,749	No cap	0
LTSS: Consumer Directed Care	Rare Service	2,286	7,529	10,764	No cap	0
LTSS: Chore Services	Rare Service	87	526	2,652	No cap	0
LTSS: Community Living Assistance	Rare Service	1,034	2,301	2,520	No cap	0
LTSS: Companion Services	Rare Service	226	5,555	6,134	No cap	0
LTSS: Environmental Adaptations	Rare Service	800	24,500	34,250	No cap	0
LTSS: PCA Assessment	Rare Service	274	277	536	277	2
LTSS: Respite Care	Rare Service	629	2,998	3,027	No cap	0
LTSS: Therapy	Rare Service	158	2,984	3,084	No cap	0
LTSS: Transitional Services	Rare Service	150	2,760	10,656	No cap	0
Misc. In-Home Services	Rare Service	936	6,644	10,019	No cap	0
Ambulance	Other	451	2,462	17,057	7,000	19
Case Management (Non-LTSS)	Other	75	1,061	10,933	1,200	604
LTSS: Home Health Services	Other	220	22,391	51,627	32,000	2
LTSS: Home Delivered Meals	Other	161	202	388	203	1
LTSS: Homemaker Services	Other	228	1,235	4,103	1,900	12
LTSS: PERS (Personal Emergency Response System)	Other	40	140	1,480	207	31
LTSS: Specialized Supplies & Equipment	Other	50	1,091	3,909	1,800	8
LTSS: Transportation	Other	115	914	4,852	3,000	7
Outpatient Mental Health & Behavioral Services	Other	162	2,398	12,255	4,500	74
Rehabilitation & Training	Other	96	1,558	27,703	3,900	28
Misc. Medicaid Services	Other	84	436	12,560	2,500	83
Undefined Services	Other	11	1,665	33,157	3,700	70

Potential Future LTSS Users

We constructed a baseline data file of Minnesotans in 2015 who could potentially be 65 and older by 2030 and use long-term services and supports in the future. We defined these potential future LTSS users as any and all Minnesotans age 50 and older in 2015. This file was a starting point for our projections into 2020 and 2030 and provided the baseline data used to project Medicaid eligibility, morbidity, and a range of other relevant economic and demographic characteristics listed in Table 2.

Data Sources

The five-year sample of the American Community Survey (ACS) is the main source of our baseline file, onto which we imputed key variables from four other data sources: the Health and Retirement Study (HRS), Minnesota data from the Behavioral Risk Factor Surveillance System (BRFSS), the Minnesota Health Access Survey (MNHA), and the Survey of Older Minnesotans (SOM). Where possible, we use data sources that provide information specific to Minnesota. This section describes the data sources we used to construct our baseline file.

2015 American Community Survey (five-year sample)

Conducted by the U.S. Census Bureau, the American Community Survey is a household survey designed as a replacement for the long form of the decennial Census and provides annual estimates on demographic, socioeconomic, and housing information. We chose the ACS as our primary data source because of its large sample size, which allows to make useful, Minnesota-specific estimates even after breaking the sample into 96 cohorts. Using the five-year ACS sample (2011–2015) further increases the precision of our estimates when broken down by cohort. Table 2 contains the full list of ACS variables in our baseline file.

2014 Health and Retirement Study

The Health and Retirement Study is a national-level, longitudinal panel study that surveys Americans age 50 and older and is conducted every two years by the University of Michigan with support from the National Institute on Aging and the Social Security Administration.[i] The HRS collects highly detailed information about older Americans' demographics, income and assets, health status, functional limitations, and health care utilization, in addition to a range of other topics related to retirement and aging. HRS data are commonly used in research related to aging and utilization of long-term services and supports. The most recent available HRS sample year is 2014. Table 2 contains the full list of variables imputed into our baseline file.

2015 Behavioral Risk Factor Surveillance System

The Behavioral Risk Factor Surveillance System (BRFSS) collects data regarding behavioral health and related risk factors, is sponsored by the Centers for Disease Control and Prevention, and is administered at the state level. We chose the BRFSS because it provides data on prevalence of chronic health conditions like stroke and diabetes and can provide data about these conditions at the state level. As shown in Table 2, we used the BRFSS to impute prevalence of stroke/diabetes into our baseline file.

2015 Minnesota Health Access Survey

The Minnesota Health Access Survey (MNHA) is a telephone survey that collects information about Minnesotans' health insurance coverage and access to and utilization of health care. The survey is conducted in partnership between the Minnesota Department of Health and SHADAC. We chose the MNHA because it is the best source for Minnesota-specific data on self-reported health status and health care utilization. As shown in Table 2, we used the MNHA to impute self-reported health status, inpatient hospitalization, and emergency department utilization into our baseline file.

2015 Survey of Older Minnesotans

The Survey of Older Minnesotans (SOM) is a telephone survey of Minnesotans age 50 and older. It is conducted every five to ten years by the Minnesota Board on Aging to monitor the needs and expectations of older Minnesotans. The survey is the best Minnesota-specific source for data about the family composition, social status and expectations of older Minnesotans. As shown in Table 2, we used the SOM to impute caregiver availability, and availability of living children into our baseline file.

Table 2. Baseline Data Sources and Variables

Data Source	Year(s)	Geography	N (50+)	Baseline Variables
American Community Survey (ACS)	2011-2015 (5yr sample)	MN	114,106	Age, sex, race/ethnicity, marital status, educational attainment, urbanicity, income, household size, employment status, health insurance coverage, home ownership
Health and Retirement Study (HRS)	2014	US	18,291	Medicaid eligibility (income, medical spenddown, assets), ADL limitations, long-term care insurance coverage, cognitive impairment, LTSS utilization (home-based, nursing facility)
Behavioral Risk Factor Surveillance System (BRFSS)	2015	MN	10,500	Diabetes/stroke
Minnesota Health Access Survey (MNHA)	2015	MN	5,531	Health status, inpatient hospitalization, emergency department utilization, Medicare supplemental coverage
Survey of Older Minnesotans (SOM)	2015	MN	4,000	Caregiver availability, living children

DEMOGRAPHIC PROJECTIONS

Starting with our 2015 baseline of potential future LTSS users, we projected mortality, morbidity, and Medicaid eligibility into 2020 and 2030. Our projections determine who from our baseline will be alive in 2020 and 2030, and among those who survive, our projections determine their morbidity status and their eligibility for Medicaid payment of LTSS. These three factors are the key factors influencing who will use Medicaid-funded LTSS in the future.

In this section, we first describe our process for projecting mortality using data from the Minnesota State Demographer and the HRS. Second, we describe our process for projecting changes in morbidity using data from the HRS. And third, we describe how we use HRS data to model Minnesota's eligibility rules for Medicaid payment of LTSS.

Creating Minnesota-specific Mortality Projections

We used the most recent population projections from the Minnesota State Demographic Center to project how many Minnesotans alive in 2015 would be alive in 2020 and 2030. Because our model assumes no net migration, we used the State Demographic Center's zero-migration population projection series.

Because the State Demographic Center's estimates of the 2015 Minnesota population differ somewhat from the estimates produced by the 2015 ACS, we began our projection process by re-weighting our baseline 2015 ACS data to match the State Demographic Center's estimate of the 2015 Minnesota 50+ population.

The State Demographic Center's projects the number of Minnesotans in each year between 2017 and 2070 by sex and one-year age cohort. We used these projections in 2020 and 2030 by sex and age and applied the 2015 income distribution by sex and age from the ACS to estimate the number of survivors in 2020 and 2030 by sex, age, and income. These estimates are shown in Table 3 and Table 4 below.

Table 3: Survivors by Sex and Income, 2020

	Female			Male		
Age in 2015	**0-100% FPG**	**101-400% FPG**	**400+% FPG**	**0-100% FPG**	**101-400% FPG**	**400+% FPG**
50-54	14,766	58,505	121,910	13,959	53,837	125,141
55-59	14,662	62,435	116,151	13,697	55,772	118,197
60-64	12,660	63,135	89,043	9,689	54,756	93,351
65-74	18,333	121,408	78,490	11,342	94,893	88,959
75-84	14,269	66,512	22,306	5,789	46,013	22,450
85+	7,863	22,892	3,494	1,221	9,881	4,081

Table 4: Survivors by Sex and Income, 2030

	Female			Male		
Age in 2015	**0-100% FPG**	**101-400% FPG**	**400+% FPG**	**0-100% FPG**	**101-400% FPG**	**400+% FPG**
50-54	13,043	55,030	114,889	12,377	45,789	115,939
55-59	11,181	53,244	109,707	8,638	45,984	106,166
60-64	8,654	51,294	79,357	6,398	40,420	76,632
65-74	10,977	80,680	60,459	5,318	51,405	59,779
75-84	4,409	20,007	8,873	1,108	9,873	5,639
85+	428	988	88	47	246	116

Projecting Mortality from Baseline to 2020 and 2030

Using these Minnesota-specific mortality predictions, we projected mortality in 2020 and 2030 in our 2015 baseline ACS dataset. In other words, we projected how many people from our dataset would die between 2015 and 2020 and between 2020 and 2030. Our mortality projection process had three steps for each projection: (i) create mortality probabilities in the HRS; (ii) impute mortality probabilities from the HRS sample into our baseline file; and (iii) using the imputed mortality probabilities, assign mortality to match the number of deaths predicted by the State Demographer's projections. This process allowed us to use national-level variation in mortality while also matching accepted state-level projections. This section details the process used to perform steps (i), (ii), and (iii) described above.

Creating Mortality Probabilities in HRS

We estimated probabilities of death as a function of a number of demographic, socioeconomic and health characteristics. Although the Urban Institute analysis also used these data to estimate mortality,[ii] too few details were included in their materials to have recreated their model directly. Nonetheless, we have built a model that is in line with previous studies that have used the HRS data to model mortality in older cohorts.[iii]

Specifically, we fit a logistic regression model of whether death had occurred by the 2006 HRS survey (~5 year mortality) and the 2014 HRS survey (~15 year mortality) using a variety of relevant demographic, socioeconomic, and health characteristics. From this model, we calculated predicted probabilities of death for each individual in the HRS cohort at year 2000.

Imputing Mortality Probabilities

Unconditional five-year mortality probabilities were imputed from the 2000 HRS dataset into our baseline 2015 ACS dataset using the following variables (at baseline): net property value, individual income, household size, age, sex, race, Hispanic ethnicity, educational attainment, marital status, personal care ADL limitation, mobility limitation, IADL limitation, Medicare coverage, Medicaid coverage, VA coverage, employment status, work hours, 2+ ADL threshold, inpatient hospitalization, health status, diabetes/stroke, and long-term care insurance coverage. The imputation was done using a predictive mean matching method, set to draw from the five nearest-neighbor observations.[iv]

Assigning Mortality

First, a set of five-year predicted death counts from our projections was matched to each observation by each observation's combination of age category (as defined at the baseline), income level (0-100% FPG, 101-400% FPG, 401+% FPG), and sex (male, female). For example, an individual (at baseline) who was 70 years old, whose income was 150% FPG, and who was female would be matched to the predicted number of deaths in five years among individuals in the baseline cohort: age 65-74, income 101-400% FPG, sex female. We term these counts "control totals."

Second, we perform the mortality assignment in six steps. In short, this process assigns mortality by cohort prioritized by each observation's mortality probability up to the point where the weighted number of predicted deaths reaches but does not exceed the number of deaths specified in that cohort's control total.

The following is a description of the six steps used to assign mortality:

1. *Perform an initial mortality assignment.*
   A random number between 0 and 1 is generated for each observation. If the random number is less than the observation's mortality probability, the observation is given a preliminary mortality assignment of 1 (death), otherwise 0 (survival).

2. *Create total mortality count by cohort based on initial mortality assignment.*
   Next, each observation with a preliminary mortality assignment of 1 is given a weight equal to their sampling weight. A total of these weights is then created by each unique combination of age category, income category, and sex category. This forms a preliminary total of the number of deaths in each cohort.

3. *Create a mortality probability inflation factor and inflate probabilities.*
   An inflation factor is created for each observation equal to their cohort's control total divided by their cohort's total mortality count from the previous step. If the control total is larger than the initial mortality count, then the inflation factor is greater than one; if the control total is smaller than the initial mortality count, the inflation factor is less than one. Each observation's imputed mortality probability is then multiplied by this inflation factor to scale up or scale down their probability of mortality.

4. *Perform second mortality assignment.*
   Each observation is given a second mortality assignment. If the observation is inflated mortality probability (from Step three) is smaller than their random number (from Step one), the observation is given a second mortality assignment of 1 (death), otherwise 0 (survival).

5. *Sort observations and create second cumulative mortality totals.*
   Observations are sorted by their age category, income category, sex, second mortality assignment, and predicted mortality probability. Based on this sorting, we use individuals' survey weights to create a cumulative weight. This is done to understand how many people in the total population are represented by the individuals in our sample for this specific cohort and based on this sorting.

6. *Perform the final assignment.*
   Each observation is given a final mortality assignment. If the observation is cumulative weight from the Step five is less than or equal to its cohort's control total, the observation is given a final mortality assignment of 1 (death). If the observation's cumulative weight is more than its control total, it is given a final mortality assignment of 0 (survival).

This process of imputation and mortality assignment is then repeated for those observations predicted to survive to 2020, imputing ten-year probabilities of mortality conditional on survival to 2020 and using control totals for 2030 mortality.

Projecting Morbidity Transitions

We projected morbidity in 2020 and 2030 using three health conditions:

- *Physical Function* Morbidity: 2+ activities of daily living (ADL) limitations
- *Chronic Disease* Morbidity: History of a Doctor's Diagnosis of Stroke or Diabetes
- *Cognitive Function* Morbidity: Scoring at or below the 25th percentile on the Total Cognitive Score

We treated each condition cumulatively, meaning that we determined that a person with 2+ ADL limitations in 2015 would still have 2+ ADL limitations in 2020 and 2030. For each condition, we imputed probabilities of gaining a morbidity, and thus only imputed probabilities for those observations that had survived to that period (2020 or 2030) and had not been previously assigned that morbidity. For example, when imputing probability of gaining our ADL morbidity in 2020, we performed the imputation for the set of observations that had not been assigned mortality in 2020 and had not been assigned the ADL morbidity in 2015.

Our morbidity imputation process followed a simplified version of our mortality imputation process where we (i) created morbidity probabilities in the HRS, (ii) imputed those morbidity probabilities from the HRS into the ACS, and (iii) assigned morbidity in the ACS dataset using that imputed probability. This section describes that process.

We performed this process in the following order: diabetes/stroke 2020, cognitive impairment 2020, ADL limitation 2020, diabetes/stroke 2030, cognitive impairment 2030, and ADL limitation 2030. We included all previously-assigned morbidities as independent variables in each successive imputation.

Modeling Medicaid Eligibility

Because of the complex rules used to determine eligibility for Medicaid payment of LTSS, we chose to model Medicaid eligibility using the Health and Retirement Study (HRS) data rather than use a simple income cutoff. This approach allowed us to more precisely determine who in our sample would potentially be eligible for Medicaid if they needed LTSS. We implemented a simplified version of Minnesota's 2016 eligibility rules using the deductions and thresholds from the 2014 eligibility rules where relevant to match our HRS sample year.

We implemented the four main calculations necessary to model Medicaid eligibility—net income, medical spenddown, home equity, and net assets—using data from the HRS including data on respondents' marital status, nursing facility utilization, earned an unearned income, net assets, housing assets and debt, spousal income and assets, health insurance premiums, and out-of-pocket medical expenditures.

POLICY OPTIONS

The Minnesota LTSS Projection Model uses the default situation the scenario of *status quo* (i.e., no policy implemented), which required us to project how many individuals would hold a long-term care insurance (LTCi) policy. We did this following the procedure described in Section three for morbidity projections, although we implemented three different scenarios: high, medium, or low take up.

Our model is used to estimate the effect of two polices on future LTSS costs incurred by Medicaid. These two policies are the introduction of two LTSS-related products in Minnesota: LifeStage and the Enhanced Home Care Benefit—embedding a home care benefit in all Medicare supplemental plans sold in Minnesota.

Users can choose from different levels of implementation (and take-up) of these policies. In particular, users will be able to choose whether the inclusion of a home care benefit in all Medicare supplement plans is implemented or not. The model also allows users to choose whether LifeStage is implemented, and if there will be high, medium, or low take-up of LifeStage.

In addition, the model allows users to define different levels of Medicaid eligibility as changing economic conditions affect individuals' income, but also affect their medical expenses. Thus, the model will allow for three scenarios of eligibility: high, medium, or low eligibility rates.

Long-term Care Insurance

LTCi is not one of the policy interventions our model evaluates, but it is an important factor influencing individuals' decision of LTSS utilization. We modeled three scenarios of LTCi coverage in population to understand how these scenarios would influence LTSS utilization and Medicaid LTSS expenditures in our projection years. We created control totals in our baseline to match known numbers of in-effect LTCi policies, and we created control totals for 2020 and 2030 for each of the low, medium and high scenarios of LTCi coverage.

This section describes how these control totals were created and how the model projects who has LTCi coverage based on these control totals.

LTCi Scenarios and Control Totals

The baseline control totals were based on the number of in-force policies in Minnesota according to the 2015 Long-term Care Insurance Experience Reports report published by the National Association of Insurance Commissioners (NAIC).[v] The total number of in-force policies in 2015 was 210,144.

We used data from the Minnesota Department of Commerce on the number of claimed long-term care insurance tax credits among those younger than 50 (8,326 tax credit claimants) to adjust this population-wide number of in-force policies to be the number of policies among those 50 and older.[vi] This adjustment puts the total number of in-force policies among those 50 and older at 201,818 at our baseline.

We disaggregated these 201,818 policies into 18 cells formed by the unique combinations of age (50-54, 55-59, 60-64, 65-75, 75-84, 85+) and income (<100% FPG, 101-400% FPG, 401+% FPG) using the distribution of LTCi policies by these cells in the 2014 HRS (the most recent available year). This disaggregation by age and income ensures that the distribution of LTCi coverage by age and income follows established national trends. These control totals are presented in Table 5 below.

Table 5. Baseline LTCi Control Totals (2015)

Age	Income (% FPG)			Total
	<100%	101-400%	401%+	
50-54	20	202	1,413	1,635
55-59	2,341	4,682	25,409	32,432
60-64	1,150	5,691	29,909	36,751
65-74	2,664	16,509	54,006	73,179
75-84	1,413	18,527	23,552	43,492
85+	1,211	6,821	6,297	14,329
Total	8,799	52,432	140,586	201,818

For our 2020 and 2030 control totals, we created three scenarios (low, medium and high) based on three different assumptions about the annual LTCi net lapse rate among our surviving baseline sample.

Table 6. 2020 and 2030 Long-term Care Insurance Scenarios

High (0% Net Lapse Rate)			
	2015	**2020**	**2030**
Policies	201,818	178,649	120,726
Deaths		23,169	81,092
Gross Lapse		18,594	41,755
Sales		18,594	41,755
Net lapse		0	0
Cumulative % Lapse		0.0%	0.0%

Medium (1% Net Lapse Rate)			
	2015	**2020**	**2030**
Policies	201,818	169,536	102,888
Deaths		23,169	79,191
Gross Lapse		18,594	42,413
Sales		9,481	22,674
Net lapse		9,113	19,739
Cumulative % Lapse		5.1%	16.1%

Low (1.75% Net Lapse Rate)			
	2015	**2020**	**2030**
Policies	201,818	162,461	87,034
Deaths		23,169	77,975
Gross Lapse		18,594	42,833
Sales		2,405	6,024
Net lapse		16,189	36,810
Cumulative % Lapse		9.1%	29.7%

To arrive at the number of in-force policies in 2020 and 2030 under each scenario, we began with the number of in-force policies in 2015. We then took the resulting number of surviving 2015 policyholders and subtracted the cumulative percent net lapse (compounded annually from 2015-2020 and from 2015-2030) to arrive at the total number of in-force policies in 2020 and 2030 under each scenario.

As shown in Table 6, the number of deaths among LTCi policyholders is a substantial driver of the reduction in in-force policies.

Based on these scenarios, we formed control totals of population-wide new LTCi policy sales among those without policies and lapse among those with LTCi coverage in the previous period.

A probability of LTCi purchase was then predicted for each observation using the regression coefficients. The same process was repeated for lapse of LTCi coverage among those with LTCi coverage in the base period.

Unconditional five-year LTCi purchase (sales) probabilities were imputed from the 2000 HRS dataset into our baseline 2015 ACS dataset for those who survived to 2020 and didn't have LTCi coverage at baseline. The same process was repeated for lapse among those with LTCi coverage at baseline.

This LTCi sales and lapse probability imputation process was repeated for 2030, adding 2030 eligibility probability and 2030 morbidity variables as independent variables in the imputation. Based on these probabilities and the control totals set for each scenario, we assign LTCi lapse or purchase using the process described previously. We then create 2020 and 2030 LTCi coverage variable based on these imputed lapses and purchases.

LifeStage Policy Description

LifeStage is an insurance policy that provides a life insurance benefit up to age 65 and a LTC insurance benefit starting at age 65. This product is expected to be attractive to consumers, as it combines two insurance products into one for a lower cost than would be expected if these two policies were purchased separately.

The target market for this policy is adults aged 35-55 with incomes between $50,000 and $500,000. The policy begins as a multi-year term life insurance product with a portion of the premium used to pre-fund the LTCi benefit. At age 65, the policyholder would continue to pay the same premium, but the life insurance benefit would end, and the LTCi benefit would begin.

Because middle-aged individuals are the target market for LifeStage and individuals typically need long-term care services primarily in old age, the effects of this product on future LTSS utilization could take more than 25-50 years to materialize. So, in order to capture the initial, potential effects of LifeStage in our model, we assume in all our scenarios that LifeStage was introduced in the year 2000.

Although the combination of a life insurance and LTCi benefit is what could make this policy attractive to individuals, for our model, only the LTCi portion is important. We used HRS data on life insurance coverage to model who would purchase LifeStage by 2020 and 2030; we used data from the HRS on regular LTCi that included nursing home and in-home care benefits to model the effect of this policy on patterns of LTSS utilization among the elderly, adjusting for other covariates. We imputed this data from the HRS into our ACS baseline, following the procedure used to assign mortality.

Creating LifeStage Scenarios and Control Totals

We base our projections on the assumption that LifeStage was introduced to the market at the beginning of year 2000. Then, in each year between 2000 and 2030, we used other assumptions about the following four factors to calculate the number of in-force policies in that year:

- Awareness: how many people are aware of LifeStage;
- Adjusted Trial: of those who are aware of LifeStage, how many would purchase a policy;
- Existing Policies: how many policies were in-force in the previous year; and
- Lapse: the proportion of existing policies from the previous period that were dropped.

We modeled three scenarios of awareness (low, medium, and high), but adjusted trial rates and lapse rates do not vary across scenarios. We modeled LifeStage in 2015, 2020, and 2030. However, since LifeStage was not an extant product in 2015, we do not consider it in modeling costs or utilization in our baseline year.

In each scenario, we modeled the target market for LifeStage as Minnesotans age 35-55 at time of purchase, with household incomes $50,000-$499,999, with at least a high school education, and who were employed full-time. This target population corresponds to the target market used in market research done in the development of LifeStage. We also assume no cannibalization of long-term care insurance (LTCi) by LifeStage, which in practical terms means we will project LifeStage coverage among those without LTCi. We also assume that those with LifeStage coverage have no incentive to drop their policies substitute for LTCi coverage, and thus we do not allow individuals to drop LifeStage and purchase LTCi in our model.

Aside from estimates of the target population, estimates of the number of in-force policies depend on assumptions about the factors described above: awareness rate, adjusted trial, and lapse rate. Because awareness, lapse rates, and the LifeStage target market are all related to age, we modeled the number of in-force policies in each year in 21 unique one-year age cohorts among those 35-55 in 2000 and thus eligible to purchase LifeStage in that year.

Awareness Assumptions

Our three LifeStage scenarios are driven only by three scenarios of awareness of the LifeStage product in the target population as shown in Table 7. These awareness scenarios based on LifeStage market research and product development from O'Leary Marketing Associates. As shown, awareness of LifeStage is at or below one percent upon introduction and doubles each year until the about seventh year of implementation when growth slows down before reaching a maximum awareness rate by 2016. This awareness rate then remains steady through our two projection years, 2020 and 2030.

Table 7. LifeStage Product Awareness (%) by Year and Scenario

Year	Low Scenario	Medium Scenario	High Scenario
2000	0.25	0.5	1.0
2001	0.5	1.0	2.0
2002	1.0	2.0	4.0
2003	2.0	4.0	8.0
2004	4.0	8.0	16.0
2005	8.0	16.0	32.0
2006	16.0	32.0	64.0
2007	32.0	40.0	70.0
2008	40.0	45.0	75.0
2009	45.0	50.0	80.0
2010	50.0	55.0	85.0
2011	50.0	60.0	90.0
2012	50.0	65.0	90.0
2013	50.0	70.0	90.0
2014	50.0	70.0	95.0
2015	50.0	70.0	95.0
…	…	…	…
2020	**50.0**	**75.0**	**95.0**
…	…	…	…
2030	**50.0**	**75.0**	**95.0**

Adjusted Trial Assumptions

We assume a constant adjusted trial rate of 20.6 percent. Although LifeStage market analysis conducted by Maddock Douglas showed that the adjusted trial varied somewhat by age and income, the range of adjusted trial between income and age groups was small (three percentage points at largest), and we determined that creating a model that would allow adjusted trial to vary by age and income would not meaningfully increase the precision of our estimates and would significantly complicate our modelling approach.

Lapse Rate Assumptions

The assumed lapse rates were those produced in actuarial analysis of the LifeStage product by United Health Actuarial Services. Per this analysis, modified life insurance lapse rates are used for the period before the product converts from life insurance to long-term care insurance at age 65 for each age cohort. After age 65, a standard long-term care insurance lapse rate of one percent is used. Separate lapse rates were used for each one-year age cohort in each year. Table 8 shows a sample of these lapse rates for policyholders ages 50-55 in 2000.

Table 8. Sample LifeStage Lapse Rates (%) by Age (in 2000) and Year

Year	Age 50	Age 51	Age 52	Age 53	Age 54	Age 55
2000	7.5	7.5	7.5	7.5	7.5	7.5
2001	5.3	5.3	5.3	5.3	5.3	5.3
2002	4.4	4.4	4.4	4.4	4.4	4.4
2003	3.7	3.7	3.7	3.7	3.7	3.7
2004	3.2	3.2	3.2	3.2	3.2	3.2
2005	2.9	2.9	2.9	2.9	2.9	2.9
2006	2.8	2.8	2.8	2.8	2.8	2.8
2007	2.8	2.8	2.8	2.8	2.8	2.8
2008	2.9	2.9	2.9	2.9	2.9	2.9
2009	3.0	3.0	3.0	3.0	3.0	3.0
2010	2.8	2.8	2.8	2.8	2.8	1.0
2011	2.9	2.9	2.9	2.9	1.0	1.0
2012	2.8	2.8	2.8	1.0	1.0	1.0
2013	3.3	3.3	1.0	1.0	1.0	1.0
2014	3.4	1.0	1.0	1.0	1.0	1.0
2015	1.0	1.0	1.0	1.0	1.0	1.0
…	…	…	…	…	…	…
2020	1.0	1.0	1.0	1.0	1.0	1.0
…	…	…	…	…	…	…
2030	1.0	1.0	1.0	1.0	1.0	1.0

Note: Line indicates year in which policy converts to LTCi at age 65.

LifeStage Control Totals

Figure 1 shows the equation used to calculate the number of in-force policies in each year.

Figure 1. Calculation of In-force LifeStage Policies

$$Policies_t = Policies_{t-1} + ((Population_t - Policies_{t-1}) \times Awareness_t \times AdjustedTrial) - (Policies_{t-1} \times LapseRate_{t-1}) - Deaths_t$$

Using this formula, we estimated that the number of in-force polices would range between 10 and 21 thousand in 2020 and between 39 and 76 thousand in 2030. Table 9 shows the control totals estimated for each projection year under each scenarios of awareness rates.

Table 9. LifeStage Control Totals, 2020 and 2030

	2020	2030
Low	9,900	39,000
Medium	12,400	52,600
High	21,400	75,700

We assume no cannibalization of the LTCi market by LifeStage and thus only impute LifeStage purchase for those who we project do not hold a LTCi policy in the relevant projection year. To this end, we imputed LifeStage and LTCi in the following sequence: 2015 LTCi, 2015 LifeStage, 2020 LTCi, 2020 LifeStage, 2030 LTCi, and 2030 LifeStage.

Assigning LifeStage Sales and Lapse

The process for assigning new purchases and lapse followed the procedure we used to assign mortality, which uses control totals to adjust the final assignment of this characteristic. We used the number of predicted new purchases and lapsed policies per one-year age cohort as control totals as described. We then combined the imputed purchase and lapse variables to create 2020 and 2030 LifeStage coverage variables.

Home Care Benefit in Supplemental Medicare Plans

Another initiative we model is based on the inclusion of an embedded Enhanced Home Care benefit in all Medicare supplemental plans. Although this initiative is still being formulated, the intention is that this would be an embedded benefit in all Medicare supplemental plans sold in Minnesota. This implies that everyone who buys a supplemental plan would have this benefit.

In our baseline imputation of who currently has a Medicare supplemental product, we created control totals of who currently has a policy based on data from the 2015 MNHA. We then impute probabilities for respondents who report having Medicare coverage in the ACS and assign Medicare supplemental coverage using these probabilities and control totals using the method previously described.

Our model projects which individuals will purchase Medicare supplemental plans in 2020 and 2030 using a similar imputation process as the one described in Section three for our morbidity indicators: (i) we created probabilities for purchasing a Medicare supplemental plan using data from the MNHA, (ii) we imputed these probabilities from the MNHA into the ACS for Minnesota residents, and (iii) we assigned Medicare supplemental plans in the ACS dataset using that imputed probability.

Creating Medicare Supplemental Control Totals

We controlled the Medicare Supplemental coverage rate to the coverage rate reported by participants of the 2015 MNHA. The MNHA is a joint project of the Minnesota Department of Health and SHADAC and is the official survey for information about health insurance coverage in the state.

We split the population into a combination of our age and FPG categories, ending up with a total of 9 sub-groups (see Table 10 below). After we restrict our sample to the 65+ population with Medicare coverage, we estimated the proportion of the population within each cell that had a Medicare Supplemental plan.

Then, using our baseline ACS file, we took this percentage and multiplied it by the number of Minnesotans age 65 or older in each sub-group who had Medicare coverage. Table 10 below shows the Medicare Supplement control totals we produced and which we use to perform our baseline Medicare Supplement imputation.

Table 10. Medicare Supplement Baseline Control Totals

Age	Income Category (% FPG)			Total
	<100%	**101-400%**	**401%+**	
65-74	26,361	195,311	155,469	377,141
75-84	23,104	139,026	51,981	214,111
85+	18,897	57,582	12,058	88,536
Total	68,361	391,919	219,508	679,788

We estimate that in 2015, approximately 679,788 elderly Minnesotans will have Medicare Supplement Plans, which represents 84.4% of the elderly population (and 86.7% of those aged 65+ who have Medicare coverage).

Medicaid Eligibility

We projected eligibility in 2020 and 2030 using three eligibility scenarios in each year (e.g. low, medium, and high rates of eligibility), designed to be selectable by the user. Our eligibility projection process had two steps for each projection: (i) impute eligibility probabilities from the HRS sample into our baseline file, and (ii) using the imputed eligibility probabilities, assign eligibility to match the predicted number of individuals eligible in the scenario.

OUTCOMES

The MN LTSS Projection Model has two main outcomes. The first is the projection of elderly Minnesotans who will require LTSS in 2020 and 2030. The second is the total costs to Medicaid to provide this care.

Population Projections and LTSS Utilization

Our model's predictions of mortality, morbidity, and Medicaid eligibility, as well as other important variables, allowed us to sort individuals in our baseline to each of the model's 96 cohorts in 2020 and 2030, identifying how elderly Minnesotans transition between these cohorts. These transitions are primarily due to changes in elderly Minnesotans' Medicaid eligibility status and number of ADL limitations.

Since the main objective of the MN LTSS Projection Model is to predict future costs to Medicaid for their elderly enrollees, we excluded three categories of individuals from our final sample. First, we excluded everyone who we determined not to be eligible for Medicaid, using the method discussed previously (this meant focusing on half of our original 96 cohorts, or only 48 cohorts). Second, we excluded anyone whose age at the time of analysis was not 65 or over. Third, we excluded individuals who were not likely to use any paid LTSS (see below for projection detail). Our final dataset included only elderly Minnesotans eligible for Medicaid who we project will utilize LTSS.

LTSS Utilization

We created two utilization variables to differentiate individuals we project as LTSS users from non-users (the third exclusion criteria): (i) use of nursing facility services and (ii) use of paid home and community-based care. Following the definition used to estimate costs for nursing home residents and using the HRS data, we defined a *nursing facility resident* as anyone who either (i) reported a current nursing facility stay of longer than 100 days or (ii) reported more than 180 nursing facility nights in the past 24 months. We defined *home-based care user* as anyone who reported receiving help with performing any activities of daily living or instrumental activities of daily living and who did not meet our nursing facility resident criteria. This division of two types of LTSS implies that we divide each of the 48 cohorts we determine being Medicaid eligible (from the original 96) into two, thus also ending with a total of 96 cohorts for the population we project will be LTSS users in 2020 and 2030.

We projected LTSS utilization (nursing facility residency, home and community-based care) in 2020 and 2030. Our LTSS utilization projection process had two steps for each projection: (i) impute utilization probabilities from the HRS sample into our baseline file, and (ii) using the imputed probabilities, assign a utilization outcome to each respondent.

Creating Predicted Utilization Probabilities

To create the predicted probabilities of our utilization outcomes we first created logistic regressions in the HRS with the utilization outcome as the dependent variable. We ran separate regressions for each of the two utilization outcomes. In each regression the following were used as independent variables: age (categorical), sex, marital status, race (white or non-white), Hispanic ethnicity (Hispanic, non-Hispanic), educational attainment, number of living children, smoking status (never smoker, former smoker, never smoker), body mass index (four categories cut at 18.5, 30 and 35 corresponding to the definitions of underweight, normal weight, overweight, and obese), level of physical activity (defined as doing physical activity more than twice in the last week), father's age at death, number of chronic conditions (capped at 4), self-rated health status, ADL limitations (0-1 or 2+), ever had stroke or diabetes, life insurance coverage, Medicaid coverage, Medicare coverage, VA coverage, employer-sponsored coverage, direct-purchase coverage, household income, household assets, employment status, and LTCi coverage. All continuous variables were made categorical with four categories defined by the 25th, 50th, and 75th percentiles of the continuous variable.

A probability of utilization was then predicted for each observation using the regression coefficients.

Imputing Predicted Utilization Probabilities and Assigning Utilization

We imputed LTSS utilization probabilities from the 2000-2006 HRS dataset into our baseline 2015 ACS dataset for those who survived to 2020. We first imputed and assigned nursing facility utilization and then imputed and assigned HCBS utilization among those who were not assigned nursing facility utilization. In each case, we used the following independent variables: vehicle ownership (baseline), net household property value (baseline, categorical with categories defined by the 25th, 50th and 75th percentiles), household income (baseline), individual income (baseline), household size (baseline), age, sex, race, Hispanic ethnicity, educational attainment (baseline), marital status (baseline), personal care ADL limitation (baseline), mobility limitation (baseline), IADL limitation (baseline), employer-sponsored coverage (baseline), Medicare coverage (baseline), Medicaid coverage (baseline), VA coverage (baseline), living children (baseline), caregiver availability (baseline), employment status (baseline), work hours (baseline), inpatient hospitalization (baseline), health status (baseline), long-term care insurance coverage (baseline), Medicaid eligibility probability (baseline), nursing facility utilization (baseline), HCBS utilization (baseline), 2+ ADL limitations (baseline), cognitive impairment (baseline), diabetes/stroke (baseline), 2+ ADL limitations (2020), cognitive impairment (2020), diabetes/stroke (2020), LTCi (2020), LifeStage (2020), Medicare Supplement (2020), and Medicaid eligibility probability (2020). The imputation was done using a predictive mean matching method, set to draw from the five nearest-neighbor observations.[vii]

This probability imputation process was repeated for 2030, adding 2020 assigned utilization (nursing facility and HCBS), 2030 morbidity, and 2030 policy variables as independent variables in the imputation.

For scenarios in which LifeStage or the embedded EHC benefit in supplemental Medicare coverage did not exist, these policy variables were dropped as independent variables from the regression. Utilization outcomes were then assigned based on these probabilities using the random assignment procedure previously described.

It is important to note that our model assumes that every individual who requires LTSS and is eligible for Medicaid will apply to get such coverage. We know that this is not the case, but our assumption is in line with the worst-case scenario in estimating fiscal projections on the potential resources needed for Medicaid in the future. Assumptions regarding variable “take-up” rates could be added to the model.

Total Cost Projections

Our model projects the number of individuals who will use Medicaid-financed LTSS services in 2020 and 2030. To produce the total cost of these services, we combined our model output with average cost data from the MMIS for each type of utilization by each of our cohorts; total costs are estimated as the product of the projected number projected to use that service (obtained from our model projections) and the average cost of the type of long-term care service (obtained from the MMIS). Similarly, these total costs can be estimated based on the key characteristics of the projected population including type of service, sex, age, urbanicity, morvidity, and race/ethnicity.

To estimate the number of individuals in each cohort that will use each type of service in each projection year, we first used a probit regression to estimate the proportion of the population in each cohort that would use each type of LTSS service and second, multiplied this proportion by the number of individuals in each cohort in each projection year.

In each probit model, the dependent variable was the type of LTSS service utilization (nursing facility or HCBS), and the independent variable was the cohort variable (cohorts 1-96). Based on the regression coefficients produced, we estimated the proportion of each cohort that utilize LTSS services. We then used this proportion to calculate the number of individuals who use LTSS in each cohort.

To produce the total cost per cohort, we estimated the average cost by cohort and calculated the product of this average cost and the number of individuals using each type of service by cohort. The total cost of Medicaid LTSS in each year is the sum of the total costs by cohort per type of service.

CONCLUSION

The MN LTSS Projection Model provides information on average and total costs using projections from the baseline 2015 LTSS costs from Medicaid claims in the MMIS (see Section two). We also are able to estimate projected costs based on key characteristics of our cohorts including type of service, sex, age, urbanicity, morbidity, and race/ethnicity.

Our model represents a work in progress. In this report, we have presented our conceptual model and detail on model inputs and projection assumptions. We use Minnesota-specific data whenever possible and national data adjusted to the characteristics of Minnesotans to aid in our development of a full projection model. Our model makes use of expert demographic projection modeling and of key variables that influence future LTSS utilization obtained from peer-reviewed literature. The use of claims data from current Medicaid users of LTSS grounds us in Minnesota-specific patterns of use of costs. As new data and evidence become available, refinement of the model is possible, and we will continue to document the model development for ongoing use by the Department of Human Services. These refinements can also be applied to model the effect of other policies or contextual scenarios.

[i] The Health and Retirement Study (HRS). https://hrs.isr.umich.edu/about

[ii] Favreault MM, Gleckman H, Johnson RW. Financing long-term services and supports: options reflect trade-offs for older Americans and federal spending. Health Affairs. 2015;34(12):2181-2191.

[iii] Feinglass J, Lin S, Thompson J, et al. Baseline health, socioeconomic status, and 10-year mortality among older middle-aged Americans: findings from the Health and Retirement Study, 1992–2002. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*. 2007;62(4):S209-S217.

[iv] Little, Roderick JA. "Missing-data adjustments in large surveys." *Journal of Business & Economic Statistics* 6, no. 3 (1988): 287-296.

[v] National Association of Insurance Commissioners. "Long-term Care Insurance Experience Reports for 2015," 2016. http://www.naic.org/documents/prod_serv_statistical_ltc_lr.pdf

[vi] We believe that 8,326 is likely a lower bound estimate of the number of LTCi policies held by those 50 and olde since not all policyholders can benefit from the tax credit. To claim the tax credit, the LTCi policy must have a benefit level of at least $100,000 and meet the IRS guidelines for deductible LTCi policies. In addition, the LTCi tax credit is not refundable and only Minnesotans with a tax liability can benefit, reducing the number of low-income policyholders who would apply for the credit.

[vii] Little, Roderick JA. "Missing-data adjustments in large surveys." *Journal of Business & Economic Statistics* 6, no. 3 (1988): 287-296.