Aging in Wyoming
Part I: Background

A PRIMER ON

DEMOGRAPHIC CHANGES

AND

PROJECTED MEDICAID LONG-TERM CARE COSTS

Wyoming Department of Health

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Wyoming Department of Health
401 Hathaway Building
Cheyenne, WY 82002
health.wyo.gov

I HAVE achieved my seventy years in the usual way: by sticking strictly to a scheme of life which would kill anybody else … I will offer here, as a sound maxim, this: That we can't reach old age by another man's road.

—Mark Twain (1905)

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Executive Summary

As a safety-net payer and provider of long-term care services, the State of Wyoming will face increasing cost pressure from the needs of our aging population. This problem is the product of five major factors:

- An aging population that is increasingly burdened with chronic disease;
- A decreasing ratio of working-age adults (and thus taxpayers, and paid or unpaid caregivers) per older individual;
- The high cost of paid long-term care;
- People who are increasingly unprepared to pay for these costs out-of-pocket, and,
- A small and weakening private long-term care insurance market.

Based on current trends, we project that Medicaid long-term care costs will roughly double over the next two decades —from ~ $125 million today to ~ $260 million by 2040.

The biggest lever that the State has in influencing these future costs is to encourage healthy aging at home by supporting long-term care in home- and community-based settings instead of institutions.

Staying at home is not only often preferable for most people, but it also represents a significant cost savings to the State.

This "Aging in Wyoming" series is broken into three parts. Part I, this primer, provides background on the problem to be solved, and the justification for the overall policy objective of helping people age in place. Parts II and III offer specific recommendations to support this objective. These include:

- Expanding financial and need-based access to home-based services through an 1115 Demonstration Waiver;

- Increasing rates for select underutilized but helpful waiver services like non-emergency transportation (NEMT) and adult day;

- Bundling transportation, adult day, meals and some limited care coordination into a per-diem rate; and,

- Exploring the potential of a State-operated Medicare Advantage Dual-Eligible Special Needs (D-SNP) plan.

Section 1. What is the problem we're trying to solve?

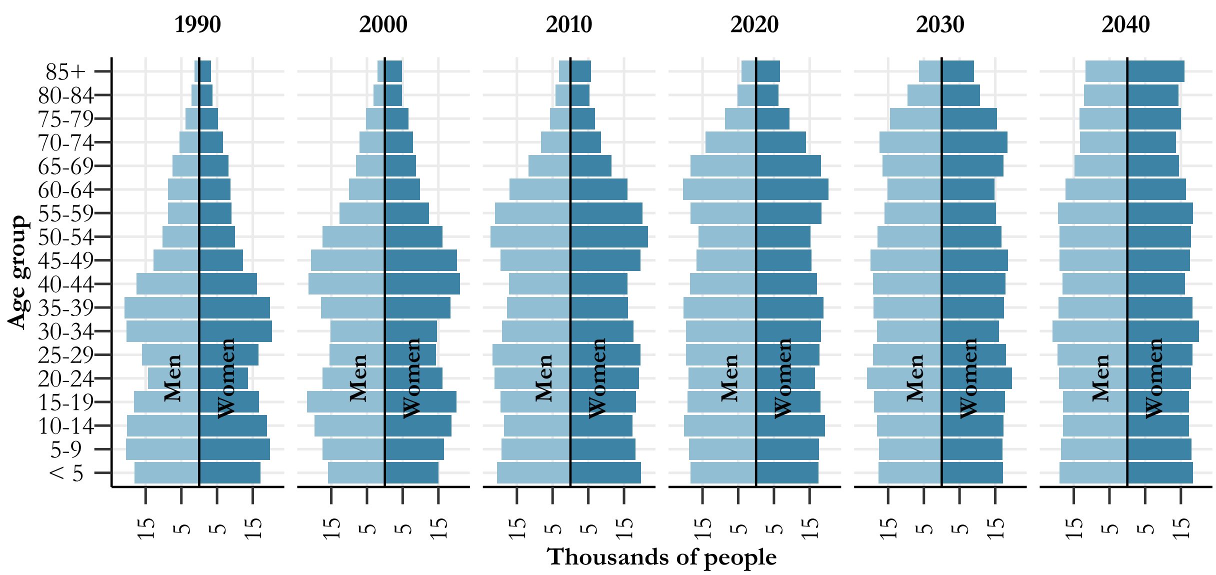
With a rapidly-aging population that is increasingly unprepared for the cost of long-term care, Wyoming's Medicaid program will shoulder a larger safety-net burden over the next twenty years.

1.1. Wyoming's population is growing older

Wyoming is in the early stages of a significant aging process. While happening more slowly than the colloquial term "silver tsunami" would imply, this demographic shift is nonetheless dramatic.

Figure 1 illustrates 50 years of this process through a series of population pyramids. On each figure, the counts of people by 5-year age group are shown stacked on top of each other and broken down by sex, with men on the left and women on the right. [1]

Figure 1: Wyoming population pyramids



Generally speaking, as societies begin to age, what were population "pyramids" begin to resemble rectangles. Figure 1 shows that Wyoming is no exception. Note in particular the "Baby Boom" generation, moving up from the 30 to 45 age group in 1990 to the 75+ group in 2040. This is the cohort that will place significant demographic strain on Wyoming's long-term care resources over the projected future.

Figure 2, on the next page, consolidates these groups into a simpler demographic picture. The left panel breaks Wyoming's demographics into five main groups:

- Children;
- Working-age adults;
- The "younger-old" (65-75);
- The "middle-old" (75-85); and,

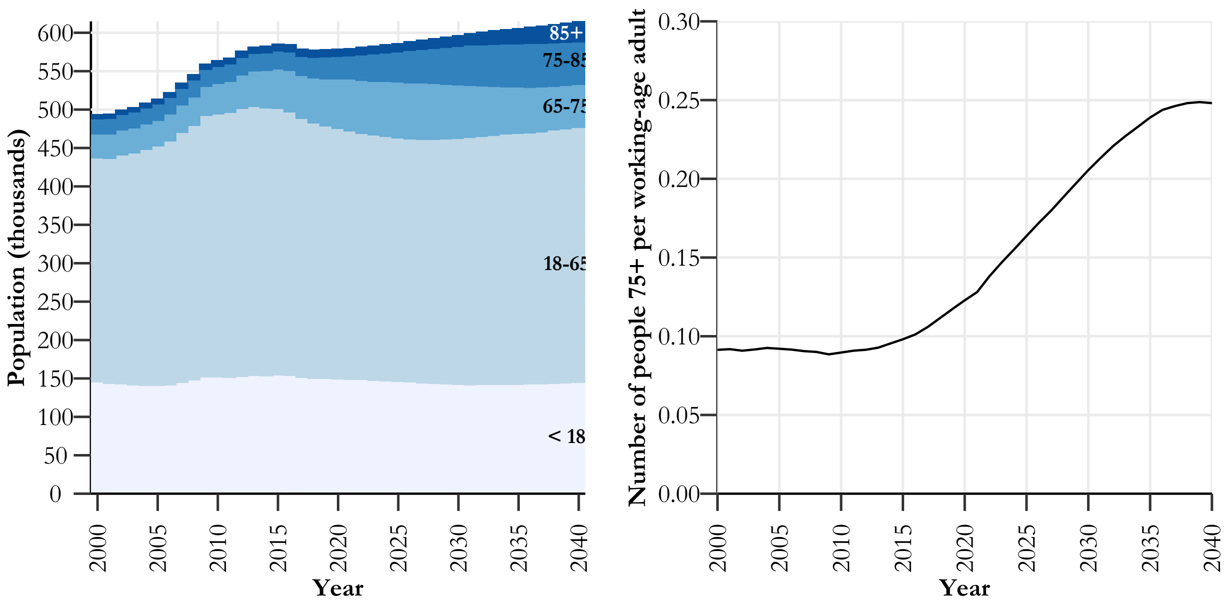
[1] Demographic data from Wyoming A&I Economic Analysis division.

- The "oldest-old" (85+).

Importantly, where the child and working-age demographics are projected to stabilize, Wyoming's oldest population will continue to increase. Our primary concern is therefore the relative growth in the middle-old and oldest-old demographics, who are at elevated risk for requiring long-term care.

The right panel of the figure shows the ratio of people over 75 to working age adults. This is known as the "dependency ratio," since it represents the average number of people likely needing the most assistance for every working-age taxpayer or (paid or unpaid) caregiver.

Figure 2: Wyoming demographics and dependency ratio



As you see on the figure, this ratio will increase dramatically between 2020 and 2038, before leveling off. This hill best evokes the "tsunami" imagery —but we are only just now beginning to experience it, and the full effects will take two decades to play out.

Figure 3, on the next page, breaks down this shift geographically, contrasting the statewide dependency ratio (black dotted lines) with the dependency ratio in each county.

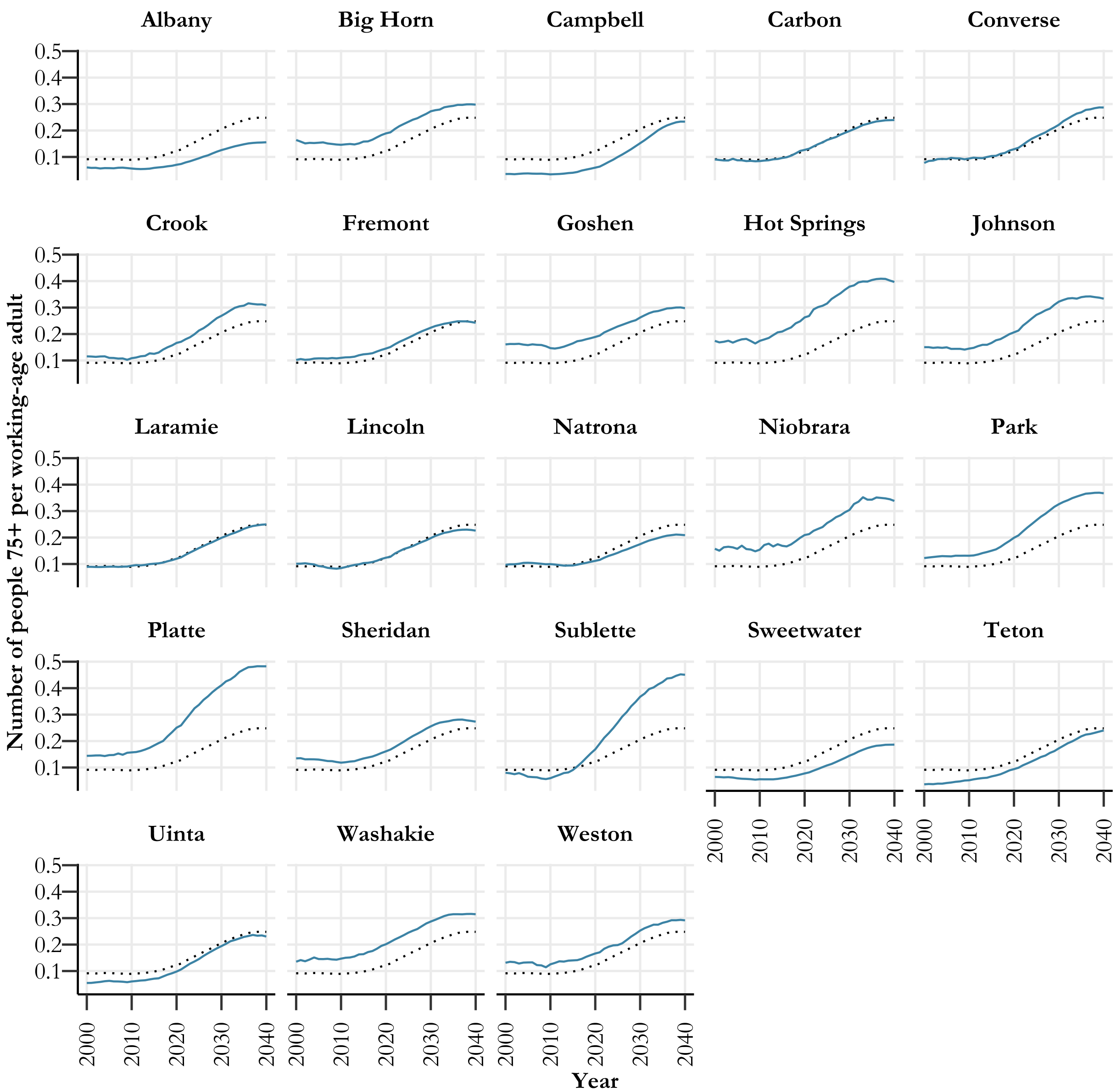
Note that some counties (e.g., Sublette, Platte, and Park) will see much greater changes in this ratio than others (Albany, Teton, and Sweetwater) over the next two decades. Other counties (e.g., Hot Springs and Niobrara) already have higher dependency ratios than the State average.

Thus, while the entire State is facing a demographic shift, the impact on taxpayers and paid and unpaid caregivers may be not be evenly distributed —and some counties may face higher stresses on local workforce than others.

1.2. Increasing chronic disease complicates long-term care

In addition to growing in number, older Americans today are increasingly burdened with chronic disease. Figure 4, on page 5, shows how the average number of chronic conditions has increased for all

Figure 3: Dependency ratio by county

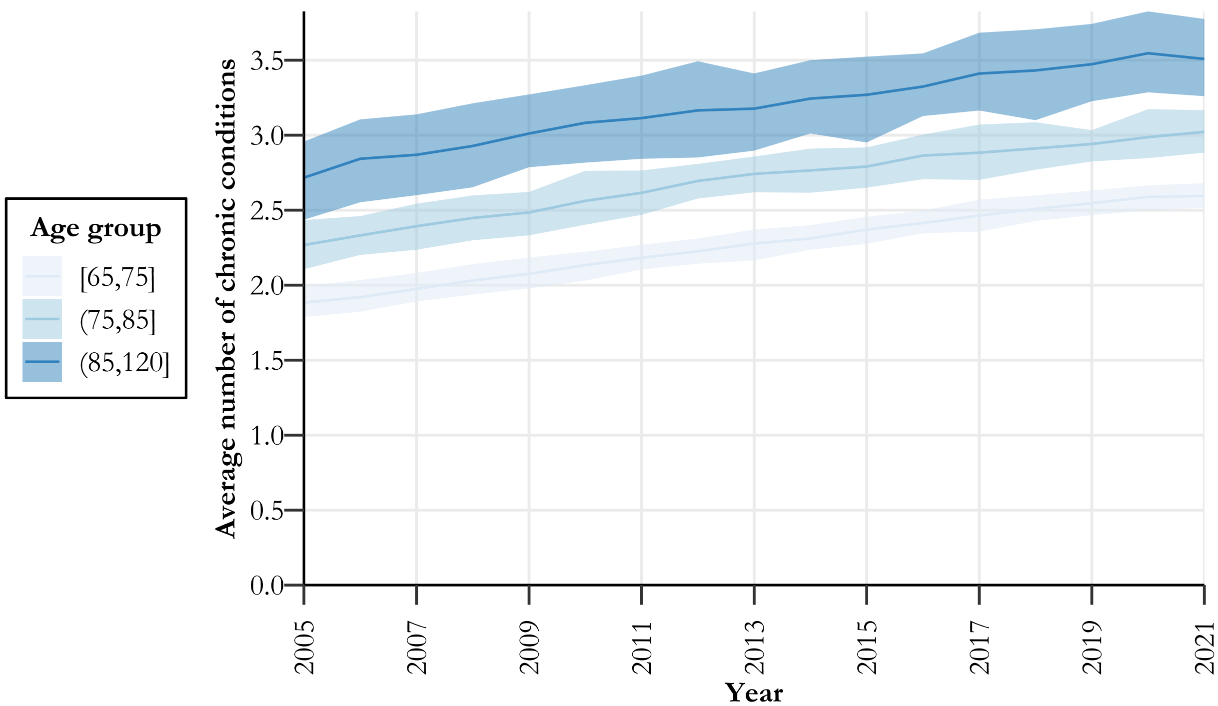


demographics between 2005 and 2020.[2]

The eight self-reported chronic conditions measured in this survey included:

- High blood pressure;
- Diabetes;
- Cancer;
- Lung disease;
- Heart problems;
- Stroke;
- Psychiatric problems; and,
- Arthritis.

Figure 4: Average count of chronic conditions by age group



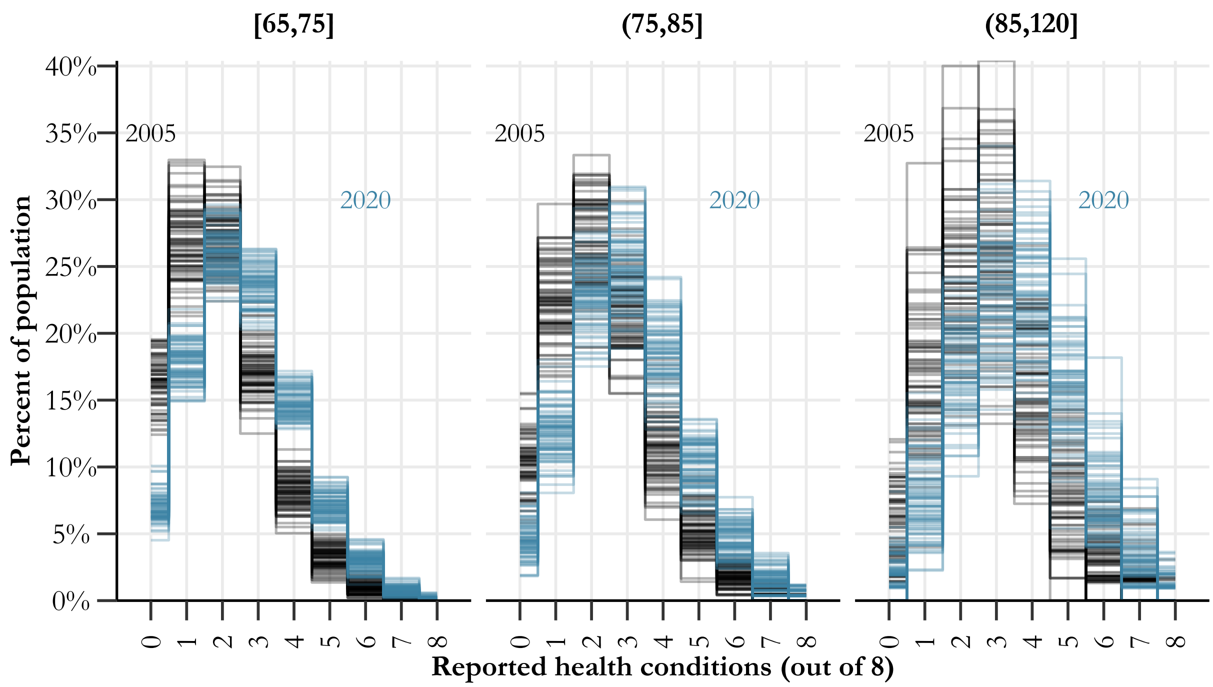
For the 65 to 75 year cohort, for example, the average number of these conditions has increased from around 1.8 in 2005 to 2.6 in 2020.

Figure 5, on the next page, shows how the *distribution* of these conditions has shifted over the same time frame. Note in particular that, for the same 65-75 cohort, the percentage of people with *zero* chronic conditions has decreased from ~ 17% in 2005 to ~ 7% in 2020.

This increasing morbidity complicates the delivery —and adds to the cost —of long-term care. A nursing home that serves severely obese nursing home patients, for example, requires investments that range from larger wheelchairs and sturdier toilets, to bariatric lifts and wider door frames.

[2] Model built on RAND Health and Retirement Survey (2018 v2), post-stratified based on demographic variables using IPUMS American Community Survey data for Wyoming.

Figure 5: Distribution of chronic conditions



Additional staffing and the increased potential for workers' compensation claims also add to costs. Since few nursing homes are willing to make these investments, severely obese patients are often unable to be quickly discharged from hospitals, resulting in longer stays in a more expensive setting.

1.3. Most people will need some form of long-term care

Of people turning 65 today, the odds of requiring *some* amount of long-term care over their lifetime —paid or unpaid —is ~ 70%.[3]

The odds of requiring *paid* long-term care of any kind is approximately a coin flip; for men, the probability of a nursing home stay is around 44% and for women, around 58%.[4]

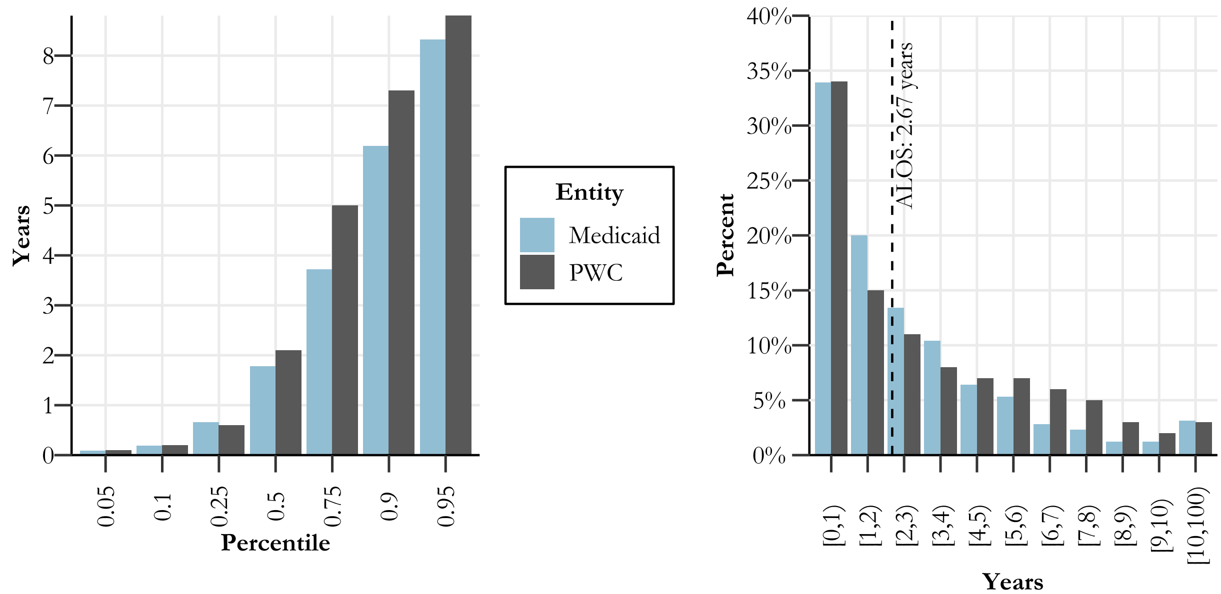
For those individuals who end up in a nursing home, the average total time spent is around 2-3 years. Note, however, the distribution is significantly right-skewed, as shown on the next page in Figure 6. This means that the average isn't particularly meaningful; a not-insignificant fraction of folks (e.g., the 5% above the 95% percentile from the left panel of Figure 6) might spend at least eight (8) years in an institutional setting. [5]

[3] https://acl.gov/ltc/basic-needs/how-much-care-will-you-need

[4] Friedberg et al. "Long-term care: how big a risk?" Center for Retirement Research. Nov 2014. https://crr.bc.edu/wp-content/uploads/2014/11/IB_14-18_508_rev.pdf

[5] Analysis of Wyoming Medicaid claims data for QMB/SLMB/Family Care Adults entering nursing home care (i.e., excluding spend-downs), compared with data from the PwC publication "Formal cost of long-term care services."

Figure 6: Nursing home average length of stay, with PricewaterhouseCoopers (PWC) estimates of the private-pay market in gray, and Medicaid estimates in blue



1.4. Long-term care is expensive

The private-pay price of a private nursing home room is approaching $100,000 per year. This fact often comes as a rude surprise, along with the realization that Medicare only covers a limited rehabilitative 100-day nursing home benefit, when people first encounter the long-term care system.

Figure 7, on the next page, shows how national median prices for various long-term care options have trended between 2004 to 2021.[6]

Most of the cost of long-term care goes to labor. Post-COVID nurse- and nurse-adjacent labor shortages have therefore impacted the entire sector. As the sharp uptick in home-based options between 2020 and 2021 suggests, this has had impacts beyond nursing homes.

In Wyoming, median 2021 prices were slightly lower than the national average, with the exception of home health:

- The median private nursing home room cost for private payers was **$91,615** per year;
- The median homemaker and home health service both cost **$66,352** per year; and,
- The median assisted living facility room cost **$50,025** per year.

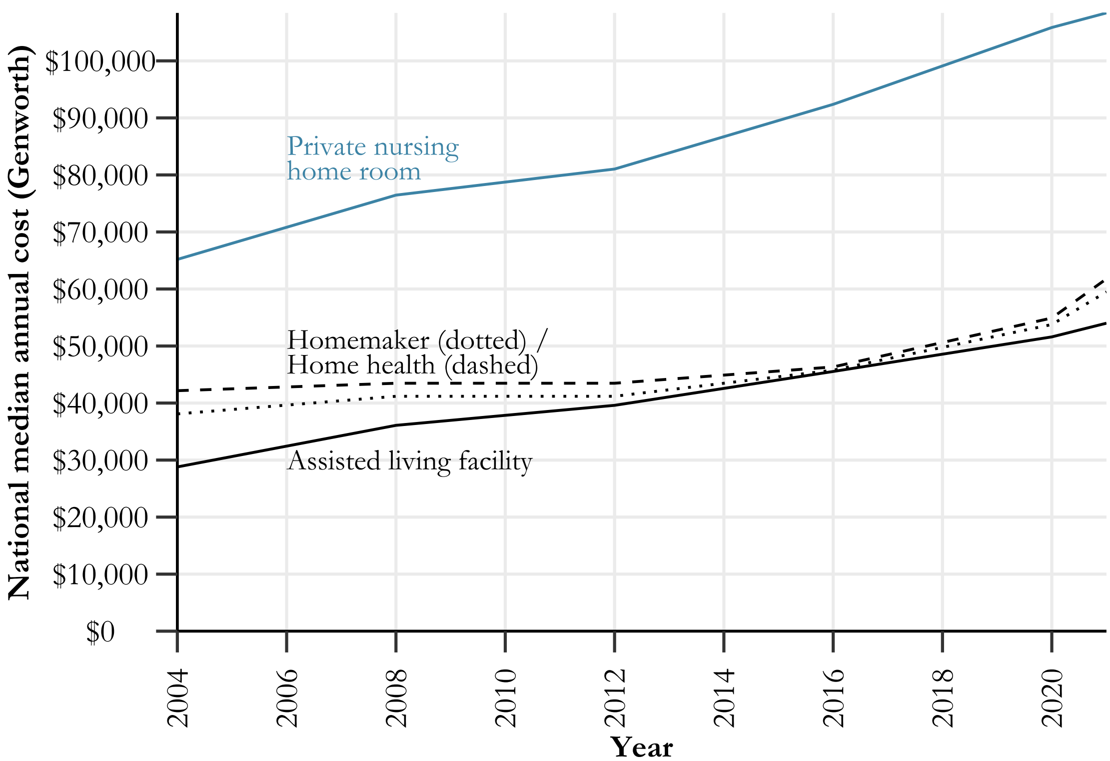
1.5. People are increasingly unprepared to pay long-term care costs

Generally speaking, the cost of long-term care is privately financed through a mix of tools:

- Income (or principal) from employer-sponsored defined-contribution plans and individual investment accounts or annuities;

[6]https://www.genworth.com/aging-and-you/finances/cost-of-care/cost-of-care-trends-and-insights.html

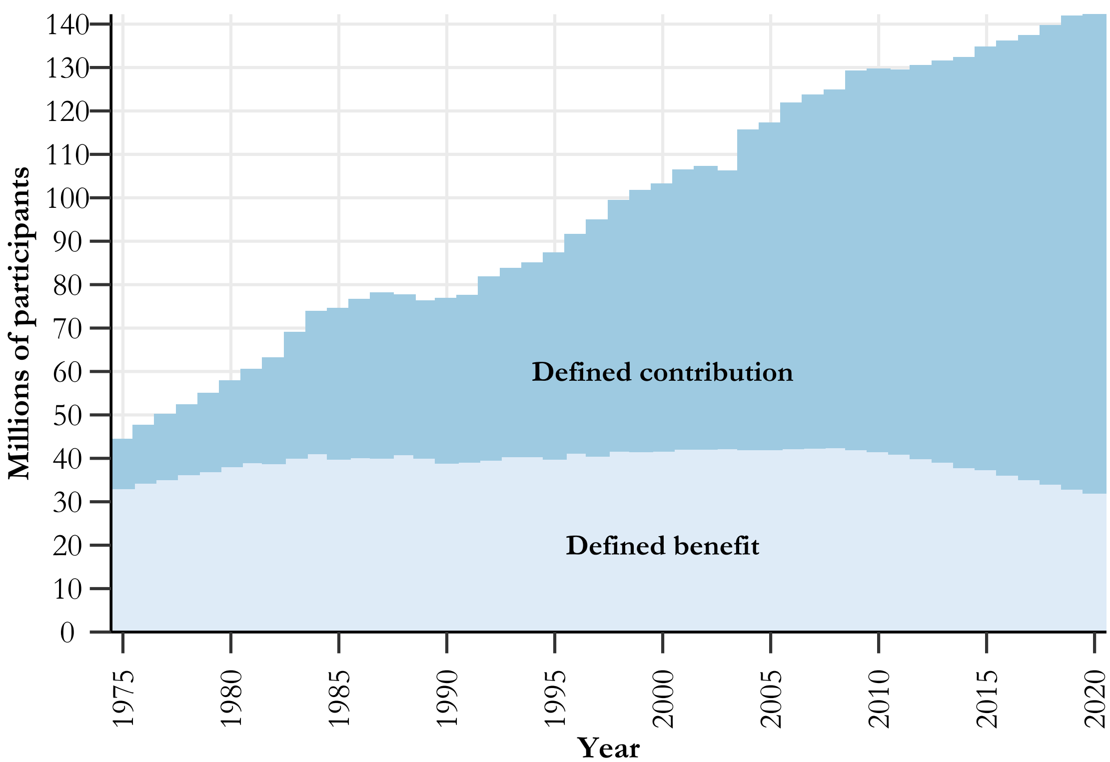
Figure 7: National median cost of care ($)



- Defined-benefit (pension) plan payments;
- Long-term care insurance (and increasingly, hybrid LTC/life insurance policies); and,
- Home equity.

Before the 1990s, most workers relied on defined-benefit (employer pension) plans for retirement security. As shown in Figure 8, however, these plans are dwindling relative to employer-sponsored defined-contribution plans (i.e., 401(k)), and will play an even smaller role in financing future generations' long-term care needs.

Figure 8: Defined benefit plans are decreasing



Newer defined-contribution plans, of course, require individuals to take responsibility for their own savings and investment strategy.

Most retirees, however, fail to accumulate sufficient assets to be able to guarantee a significant cash flow in retirement. A 2015 analysis of Survey of Consumer Finances (SCF) data by the Government Accountability Office [7] found that:

- Approximately 41% of households between the ages of 55 and 64, and 52% of households between the ages of 65 and 74, have *no* retirement savings.
- 27% of households between the ages of 55 and 74 have neither retirement savings nor a defined-benefit plan. Further, households between the ages of 55 and 64 had a median net worth of $9,000,

[7] Government Accountability Office. "Most households approaching retirement have low savings." GAO-15-419. May 12, 2015. http://www.gao.gov/products/GAO-15-419

and median home equity of $53,000.

- Of those with some retirement savings, the median amount was $104,000 for households between the ages of 55 and 64, and $148,000 for households between the ages of 65 and 74. These assets represent an inflation-protected cash flow of approximately $3,720 to $7,788 per year.
- Social Security makes up an average of 52% of household income for households over age 65.

These figures indicate that, for the average retiree, accumulated personal assets will not provide sufficient cash flow to pay for the annual costs of long-term care, even in the least-expensive settings. This increasing financial fragility is reflected in the growing number of people over 65 who are still in the workforce, which has gone from 12.5% in 2000 to 18.6% in 2016.[8]

1.6. The private long-term care insurance market is under stress

The primary alternative to "self-insuring" for long-term care is private long-term care insurance. This is becoming less and less of a viable option.

The unfortunate truism about long-term care insurance is that "if you can afford it now, you won't need it later, and if you'll need it later, you can't afford it now"[9]. In other words, people who can afford the premiums and have the foresight to purchase long-term care insurance have often accumulated enough assets to self-insure much of their long-term care anyway.

The outlook for this industry is not reassuring. Few people have long-term care insurance policies and fewer people are purchasing them each year. Wyomingites are no exception to the national trend. In 2021, the National Association of Insurance Commissioners (NAIC) estimated the total number of covered lives in the State at 10,144 — down from 2015 numbers of 11,050.[10]

Figure 9, on the next page, shows how the total number of lives covered by long-term care insurance nationally has plateaued since the mid-2000s.[11] This stagnant and rapidly-aging base of covered lives has manifested itself in the disturbing trend shown on the right panel of the figure: incurred claims significantly outpacing earned premium.

As a result, many smaller long-term care insurers have disappeared or been acquired by larger firms. The biggest industry players like Genworth have managed to stay afloat by diversifying their product lines (e.g. hybrid life insurance, mortgage insurance), drawing on investment earnings and reserves, and sharply raising premiums.[12] Raising prices, of course, will only accelerate the shrinking of the market by chasing away potential new policyholders. It is unlikely that standalone long-term care insurance products will play much of a role for most Wyomingites in the future.

[8] "The New Reality of Old Age in America." Washington Post. Sept, 2017. https://www.washingtonpost.com/graphics/2017/national/seniors-financial-insecurity

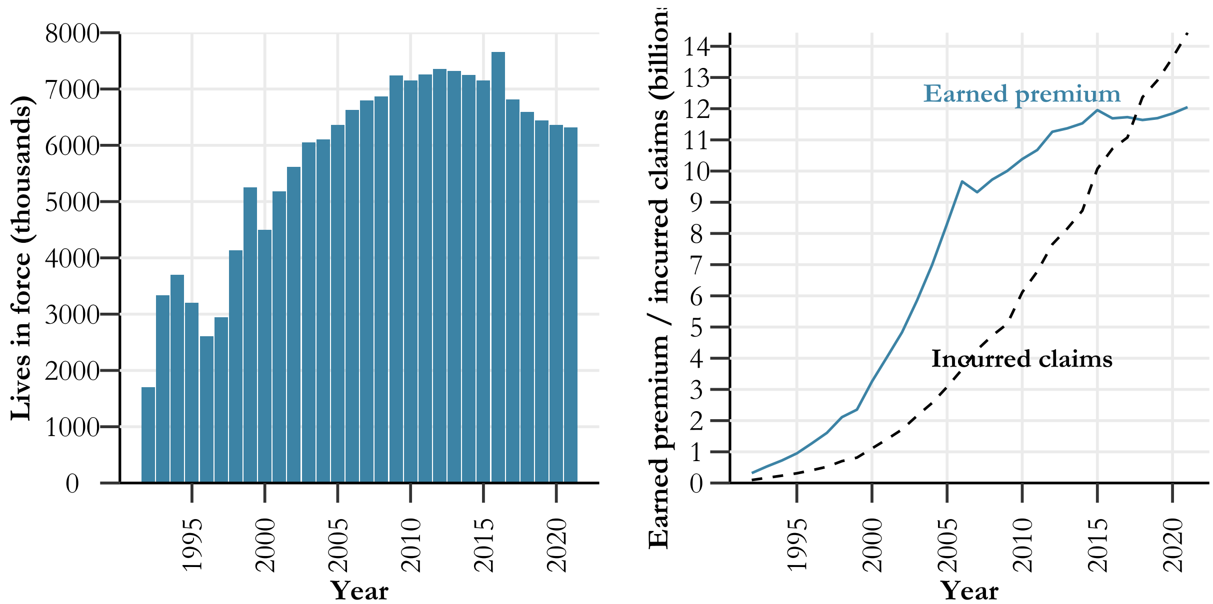
[9] Allen, James. Nursing Home Administration. Springer Publishing, 2016. pg. 351

[10] National Association of Insurance Commissioners, Long-term care insurance experience reports. 2015. http://www.naic.org/documents/prod_serv_statistical_ltc_lr.pdf

[11] Center for Insurance Policy and Research. The State of Long-Term Care Insurance. May 2016. https://content.naic.org/sites/default/files/inline-files/cipr_current_study_160519_ltc_insurance.pdf, with recent Long-term care insurance experience reports from NAIC filling in gaps from 1994 - 2021. https://naic.soutronglobal.net/Portal/Public/en-GB/RecordView/Index/4726

[12] See page 9 of Genworth's 10K filing for 2023: https://investor.genworth.com/sec-filings/annual-reports/content/0001193125-23-053994/0001193125-23-053994.pdf

Figure 9: Long-term care insurance market trends



1.7. Who's left holding the bag?

All of these factors —an aging and increasingly sick population that is increasingly unprepared for retirement, combined with the high cost of long-term care and the decline of private insurance alternatives —means that a growing majority of older people will ultimately rely on public long-term care assistance.

In Wyoming, that means an increasing reliance on Medicaid and other Department of Health long-term service and support programs. These are described in the next section.

Section 2. Medicaid long-term care options

Medicaid is the primary payer of long-term care services in the State, covering approximately 64% of all nursing home bed-days. In addition to Skilled Nursing Facility (SNF) care, Medicaid also serves elderly and disabled members through a home- and community-based services program known as the Community Choices Waiver (CCW).

Medicaid also used to operate a program in Laramie County called the Program for All-Inclusive Care of the Elderly (PACE), but this program was eliminated by budget cuts in 2020. More information on the PACE program can be found in Part III of this series.

2.1. Enrollment and cost history

Medicaid's long-term care enrollment since 2016 is illustrated in Figure 10, on the next page. In the top panel, enrollment is stacked by program; the bars add up to the total enrollment of around 4,000 members. Note that the COVID pandemic (the start of which is shown by the dashed red line) has significantly impacted trends, particularly for nursing home, where in the small bottom panels, you can see how enrollment has continued to decline from ~1,700 people in 2017 to ~1,300 people today.

Some of this enrollment decline is due to COVID mortality, particularly from the big wave in the winter of 2020 - 2021. However, as illustrated in the methodological section of this report, there was also a significant drop in the number of new *arrivals* to Medicaid long-term care.

It's unclear what is causing this effect —facility-based restrictions during the public health emergency certainly made nursing homes significantly less hospitable, for instance —but we assume the effect on arrivals will likely wear off over time.

For those readers that prefer tables, Table 1 shows enrollment and costs, both on an aggregate and per-member per-month basis, for nursing home members. Table 2 shows the same information for the Community Choices Waiver.

Note from these tables that the home-based waiver program is significantly less expensive on a per-member per-month (PMPM) basis than nursing home for the State to operate. Staying at home is also preferred by most people who need long-term care.

Increasing the percentage of Medicaid long-term care members served in home-based settings is thus the *single most important policy lever* the State can pull when it comes to controlling long-term care costs.

Figure 11 shows how this critical percentage has changed over time. Since the wait list was removed from home-based services in 2013, its share of the long-term care population has steadily increased to around 65% today.

Unfortunately, our projections show that this trend, absent any policy interventions, may be running out of steam, particularly as older demographics —whose needs may be greater than home-based services can safely meet —become a larger share of Wyoming's population.

Figure 10: Medicaid enrollment

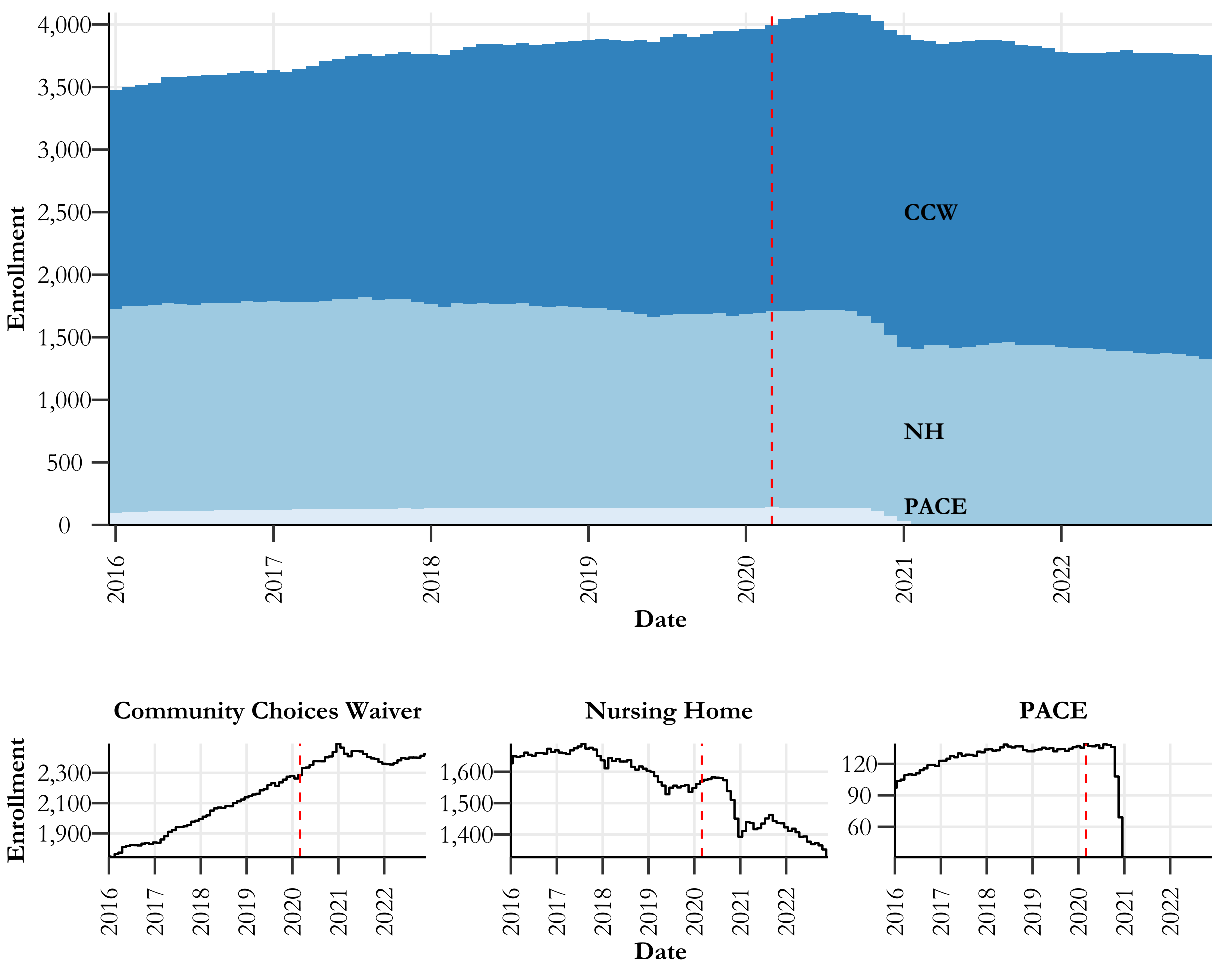


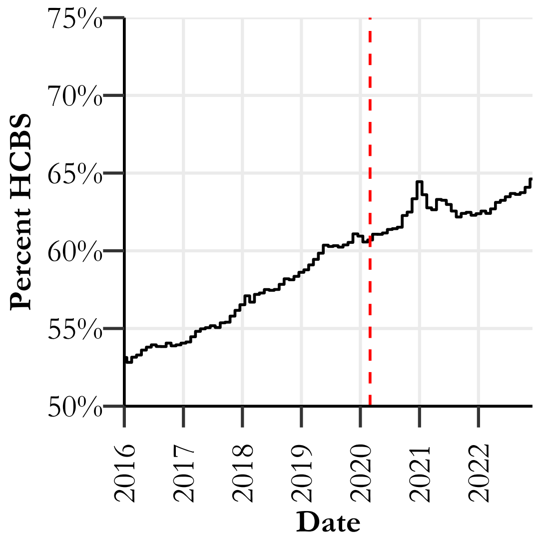
Table 1: Nursing home enrollment and costs

SFY	Expenditures	Member Months	Enrollment	PMPM
2011	$79,967,179	20,307	1,692	$3,938
2012	$79,243,110	20,569	1,714	$3,853
2013	$77,134,902	20,232	1,686	$3,813
2014	$75,382,096	20,092	1,674	$3,752
2015	$74,242,244	19,667	1,639	$3,775
2016	$88,192,883	20,250	1,688	$4,355
2017	$89,955,370	20,592	1,716	$4,368
2018	$88,245,514	19,961	1,663	$4,421
2019	$87,178,360	19,302	1,608	$4,517
2020	$94,184,437	18,864	1,572	$4,993
2021	$78,498,772	17,553	1,463	$4,472
2022	$79,011,773	17,256	1,438	$4,579
2023	$81,953,885	16,620	1,385	$4,931

Table 2: Community Choices Waiver enrollment and costs

SFY	Expenditures	Member Months	Enrollment	PMPM
2011	$31,663,825	19,203	1,600	$1,649
2012	$33,821,599	18,812	1,568	$1,798
2013	$30,383,671	18,152	1,513	$1,674
2014	$30,236,004	18,369	1,531	$1,646
2015	$32,719,341	19,776	1,648	$1,654
2016	$37,126,339	21,642	1,804	$1,715
2017	$38,522,589	22,865	1,905	$1,685
2018	$40,442,652	24,202	2,017	$1,671
2019	$43,537,210	25,476	2,123	$1,709
2020	$47,556,361	27,192	2,266	$1,749
2021	$50,059,831	29,112	2,426	$1,720
2022	$53,116,074	28,812	2,401	$1,844
2023	$54,432,132	29,100	2,425	$1,871

Figure 11: Percent of Medicaid long-term care enrollment in home- and community-based settings, with the red dashed line indicating the beginning of the COVID pandemic



2.2. Enrollment and cost projections

For all the reasons we've elaborated in the first sections of this report, we anticipate significant growth in Medicaid long-term care programs in the future.

Figure 12 shows monthly enrollment trends for the two primary programs —the home-based waiver in shown in green and nursing home is in yellow —with our projections shown as the dotted line and shaded 90% uncertainty areas.[13] Figure 13 shows the trends of per-member per-month (PMPM) cost for each program.

Generally speaking, increases in these costs have come from legislatively-mandated rate increases; there is no inherent inflation adjustment in Medicaid. In the model that generated the projections in this figure, we assume linear increases over time consistent with past trends.

When we combine monthly enrollment times the PMPM cost, we get total projected cost, shown in Figure 14. In this figure, nursing home costs are in yellow, CCW costs are in green, and total costs (the two added together) are in gray.

Ultimately, we project that Medicaid long-term care costs will roughly double over the next two decades —from ~ $125 million today to ~ $260 million in 2040.

Note how we expect nursing home and home- and community-based service enrollment to grow on roughly parallel tracks. Figure 15 extends Figure 11 to show the projected trend in the percent of Medicaid members served in home-based settings (i.e., the Community Choices Waiver). As you can see on the figure, this percentage will likely stagnate around 65%, absent any policy shift.

The likely explanation for this flattening is the slow takeup of home-based services among the oldest de-

[13] Unfortunately, this shaded uncertainty is likely too narrow, since we were unable to incorporate any uncertainty from the demographic projections that drive the arrivals model

Figure 12: Enrollment projections

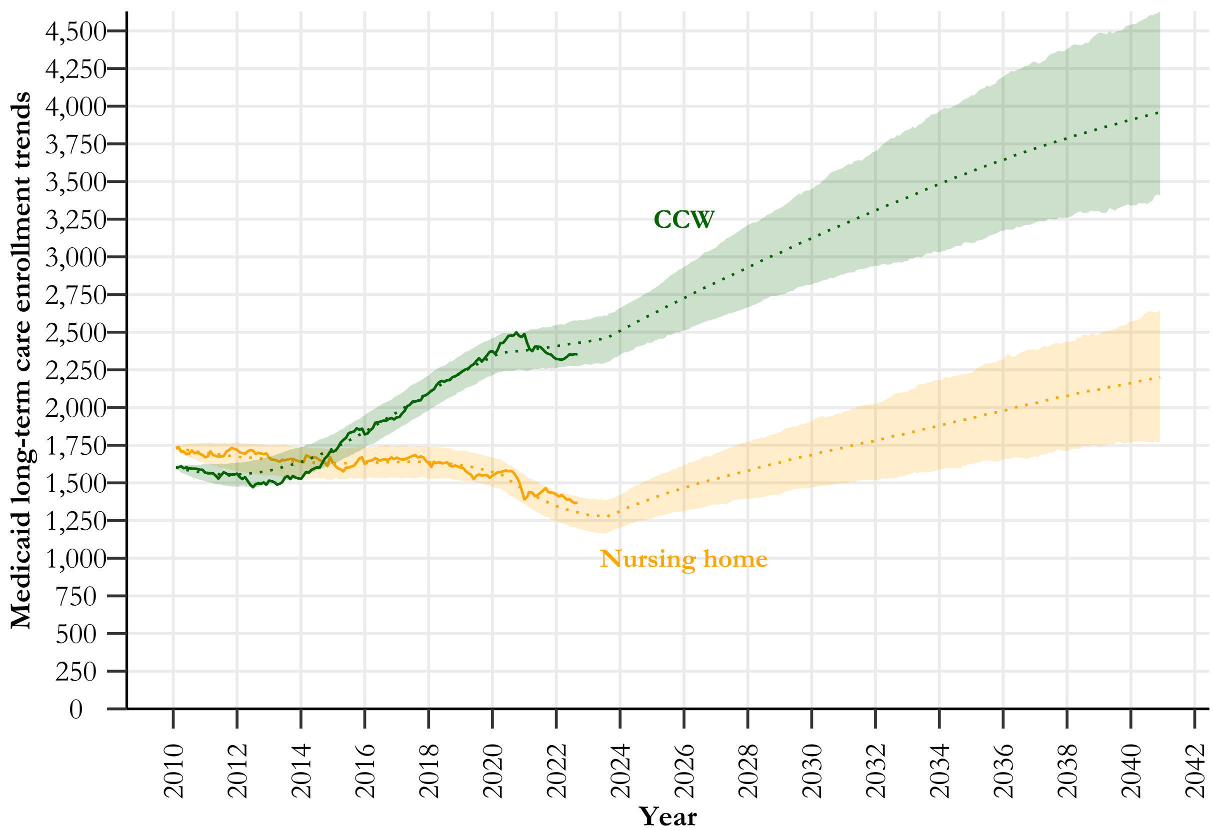


Figure 13: Per-member per-month projections

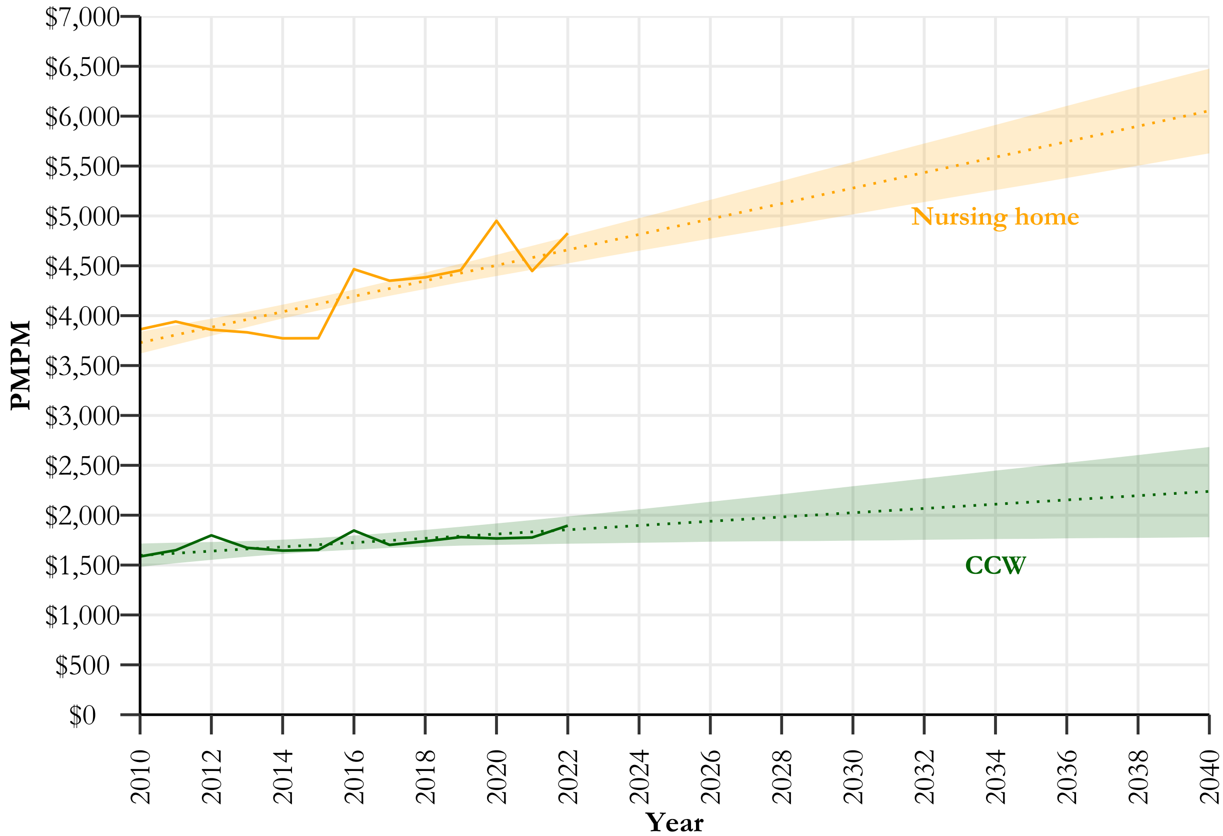
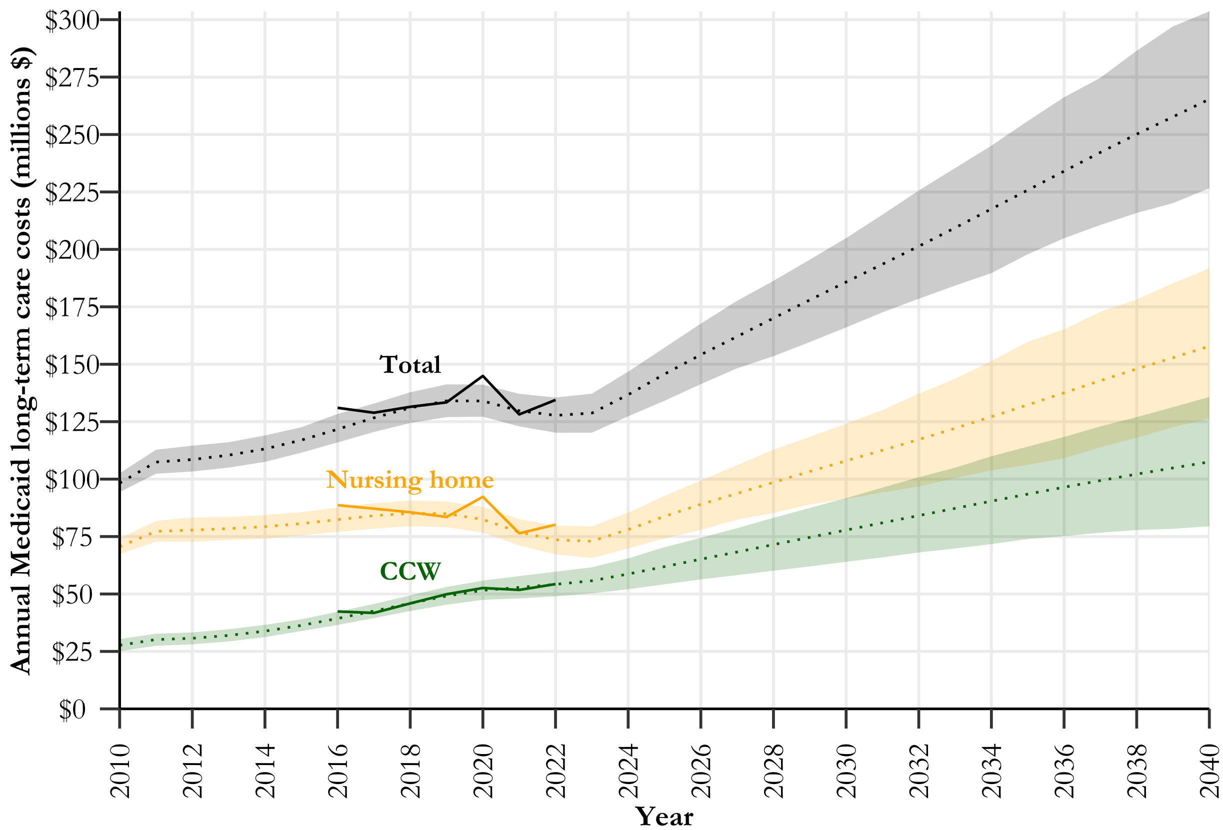


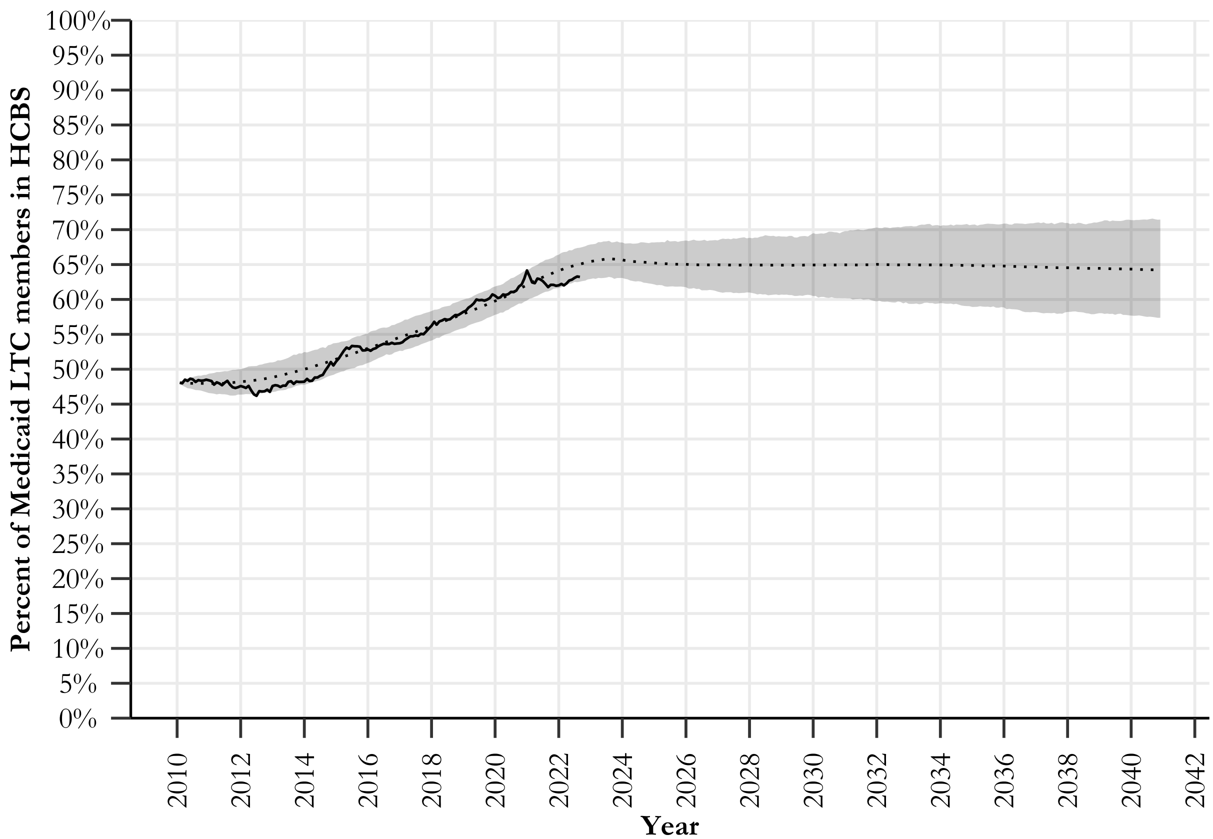
Figure 14: Total cost projection



mographics, combined with the baby-boom demographic bulge moving into those oldest demographics over the projection period.

We have more details on these projections in the technical appendix.

Figure 15: Projection of the percentage of people in HCBS



Section 3. Technical appendix

This section describes how we projected Medicaid long-term care enrollment out to 2040. This is primarily for the nerds. Most readers can stop here, if you haven't already.

3.1. Enrollment projection framework

We use a system dynamics framework to project enrollment; basically, instead of looking at enrollment directly, we model it indirectly as a "stock" with incoming and outgoing "flows."

Think of the framework as a bathtub, where Medicaid enrollment is the water level in the tub at any given time. That water level changes based on three factors:

- How much water was in the tub when the simulation started,
- How much water is coming through the tap; and,
- How much water is leaving through the drain.

Now imagine *two* bathtubs —one for nursing home enrollment and one for home- and community-based service enrollment. Both are fed by an overall supply line that first meets a diverter valve that allocates the water between the two bathtubs. Both tubs then drain independently.

This is the overall framework shown in Figure 16.

It begins with the "supply line" at the top —the number of people arriving in to Medicaid long-term care each month. This count of people is based on:

- Underlying demographic population trends based on Census data (white);[14] and,
- The rate of new arrivals per person in the underlying population (light blue).

We then model the "diverter valve" as the percent of those arrivals that go to home- and community-based long-term care (the Community Choices Waiver, or CCW) instead of nursing home (dark blue on the figure);

Finally, we model the rate the two "bathtubs" drain as a function of how full full each "bathtub" is. In other words:

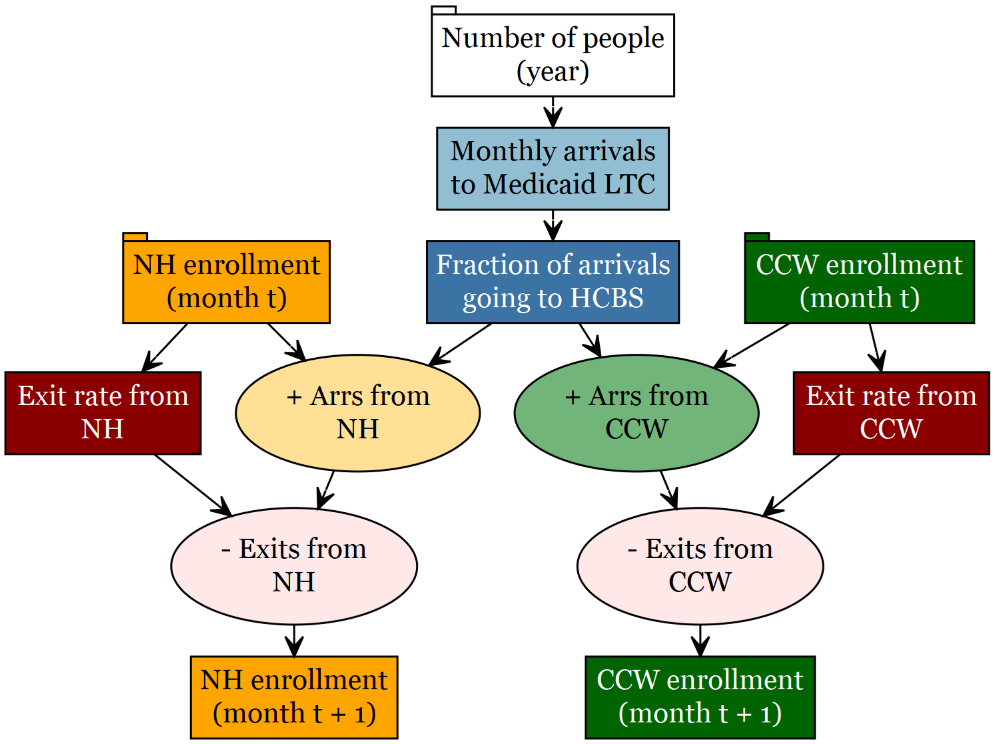
- A model of how many nursing home enrollees leave eligibility each month; and,
- A similar model of the exit rate for CCW members (dark red).

Importantly, this figure only shows one step of a larger simulation for all demographic groups. So now imagine there are "supply lines" and "diverter valves" and "drains" for 70-75 year-old women, 85+ year old men, and so on.

We gloss over the fact that some exits by demographic are actually arrivals to a new demographic, as people age, i.e. move from the 50-55 year-old group into the 55-60 year-old group, without actually leaving Medicaid generally. We make it work by truing up the arrivals, exits and enrollment levels in the underlying data to make sure everything added up, but a better (and more complex) model would have accounted for this separately.

[14] Department of Administration and Information, Economic Analysis Division. http://eadiv.state.wy.us/

Figure 16: Model framework



Moving past this ridiculous plumbing analogy and restating, we start the simulation using actual Medicaid enrollment from both groups in February of 2010 as initial values. For each iteration, the simulation moves one month at a time until it reaches the end of 2040, with the following steps:

- Generate arrivals to Medicaid LTC based on the demographic population and arrival rate at that time;
- Allocate those arrivals into CCW and nursing home;
- Evaluate how many people would have exited from both groups using the modeled exit rates and enrollment from the previous month;
- Add the new arrivals to previous enrollment and subtract the exits in order to get the new enrollment.
- Start over with the next month.

We ran 500 iterations of this simulation to include the uncertainty inherent in the models.[15] These enrollment projections are then combined with the PMPM projections to estimate total costs.

The models themselves are described in the next sections.

[15] Unfortunately, even these estimates are too narrow; since our demographic population projections come from an outside source, we could not add in the uncertainty there.

3.2. Arrivals model

We model the count of arrivals to Medicaid long-term care in month i for each five-year age/sex demographic group j using a Generalized Additive Model (GAM) framework. This allows us to model trends (for example, over time) more flexibly than with linear regression. The model uses a Poisson distribution, since arrivals are counts, and we use the underlying population of group j in month i as an offset/exposure so the model is looking at arrival rates per the number people in the demographic.

$$
\begin{aligned}
\text{Arrivals}_{ij} &\sim \text{Poisson}\left(\lambda_{ij}\right) \\
\log(\lambda_{ij}) &= \alpha + \alpha_{[\text{COVID}\times j]} + t2^{gp}_{re}(\text{Month No.}_{\cdot i}, j, \tau) + \text{offset}(\log(\text{Population}_{ij}))
\end{aligned}
$$

Here, the rate parameter λ_{ij} is estimated using a tensor product smooth (allowing both main effects and interactions between variables measured on different scales) that includes (1) a Gaussian process representing a time trend and (2) a varying effect for each demographic group j.

We also add varying intercepts for the interaction of a COVID indicator and each demographic group ($\alpha_{[\text{COVID}\times j]}$), since COVID affected age groups very differently.

In order to make computation easier for the Markov Chain Monte Carlo (MCMC) sampler, as well as induce some skepticism of large effect sizes, we set regularizing priors on all parameters:

$$
\begin{aligned}
\alpha &\sim \mathcal{N}(0, 1) \\
\tau &\sim \text{Student}(3, 0, 1) \\
\alpha_{[\text{COVID}\times j]} &\sim \text{Student}(3, 0, 2.5)
\end{aligned}
$$

The (lightly-edited to ensure it fits on the page) model output is shown below.

Note in the syntax of the R package *mcgv*, we modeled the time trend as a Gaussian process smooth with a stationary Matern kernel ("-3" in the m argument), and a range parameter of 12. This parameters were specifically chosen based on the assumption that long-term care arrivals were affected by COVID, but wouldn't increase or decrease over time.

```
 Family: poisson
  Links: mu = log
Formula: ArrivalsTotal ~ 1 + (1 | COVID:DemoGroup) + t2(MonthNo, DemoGroup,
                             bs = c("gp", "re"), m = list(c(-3, 12), NA)) +
                             offset(log(Population))
   Data: nh_model (Number of observations: 3648)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smooth Terms:
                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(t2MonthNoDemo_1)     0.32      0.06     0.22     0.44 1.00      634     1188
sds(t2MonthNoDemo_2)     7.14      1.53     4.97    10.97 1.00      269      461
```

```
Group-Level Effects:
~COVID:DemoGroup (Number of levels: 48)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.16      0.04     0.09     0.25 1.00      645      885

Population-Level Effects:
          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept    -7.78      0.38    -8.37    -6.87 1.01      187      240

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
```

Figure 17 shows how the modeled arrival rates (blue lines and shaded blue areas indicating 95% uncertainty regions) fit the count of arrivals for each demographic.

Not shown are the predictions (i.e., including the uncertainty), but the fit with the Poisson distribution is good; we don't need to rely on a more flexible distribution of counts like the negative binomial.

On the figure, note how the effect on arrival rates of the COVID pandemic vary by demographic group, with the oldest (85+) being most affected. We're not certain why COVID had such a sustained impact on Medicaid long-term care arrivals; it could be that mortality increased in the "feeder" populations, or it could be that people became much more reluctant to enter long-term care due to labor shortages and COVID restrictions. These missing arrivals may be relying more on family caretakers, for example.

Whatever the reason, we assume the "COVID effect" on arrivals will not be permanent. In our model, this effect dissipates by 2024, and the pre-COVID trend resumes for each demographic group.

3.3. Percent HCBS model

Once people "arrive" from various demographic groups in our enrollment simulation, they select either nursing home (NH) or home- and community-based services (HCBS).

We model this selection as the probability p_{ij} that the previously modeled Arrivals_{ij} in each demographic group j and month i go on the Community Choices Waiver (CCW), Medicaid's flagship for HCBS services.

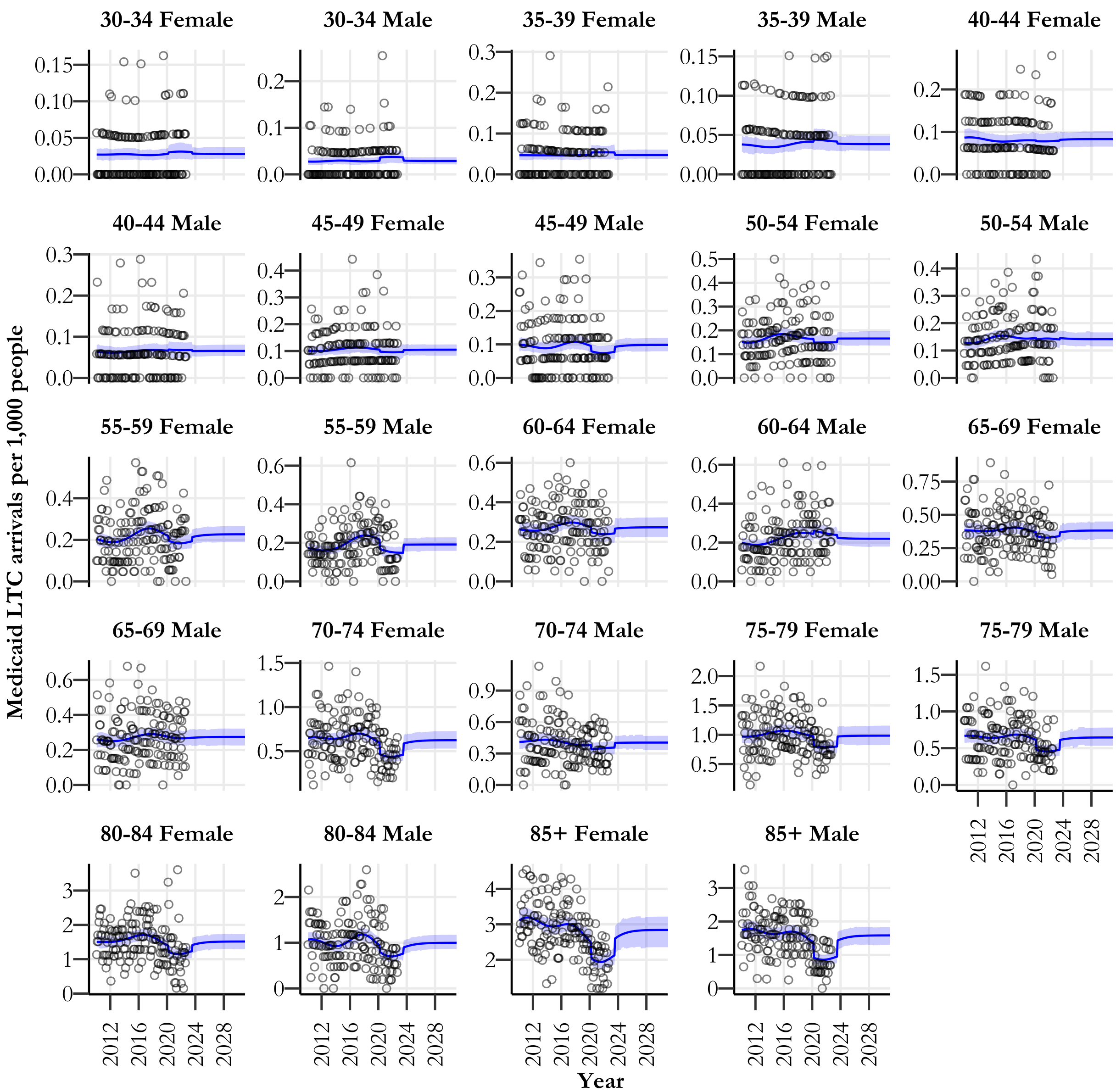
$$\text{CCW}_{ij} \sim \text{Binomial}\left(p_{ij}, \text{Arrivals}_{ij}\right)$$

$$p_{ij} = \frac{\text{logit}^{-1}(\alpha_j)}{1 + e^{1-(\text{logit}^{-1}(\beta_j)\times(\text{Month No.}_i + e^{\delta_j}))}}$$

We assume this probability p_{ij} follows an S-shaped "technology adoption" curve controlled by three parameters, α_j, β_j, and δ_j. These parameters affect:

- The level at which HCBS take-up ultimately plateaus;
- How fast the curve grows towards that plateau; and
- Any shifts in the timing of that growth.

Figure 17: Arrivals by demographic



For ease of computation, the model formula wraps these parameters in inverse logit ($\text{logit}^{-1}(x)$) or exponential (e^x) functions, so the sampler is unconstrained while parameters are ultimately constrained to be either between 0 and 1 (in the case of the inverse logit) or strictly positive (exponential).

Each of these parameters is fit to the data we observe from past Medicaid enrollment trends using the same tensor product smooths that model the interaction between age (i.e., continuous between 65 and 120) and sex.

This allows us to share information between demographic groups (e.g. 65-70 year-olds are assumed to be more similar to 70-75 year-olds than they are to those over 85).

$$\alpha_j = \alpha_\alpha + t2^{tp}_{re}(\text{Age}_j, \text{Sex}_j, \tau_\alpha)$$
$$\beta_j = \alpha_\beta + t2^{tp}_{re}(\text{Age}_j, \text{Sex}_j, \tau_\beta)$$
$$\delta_j = \alpha_\delta + t2^{tp}_{re}(\text{Age}_j, \text{Sex}_j, \tau_\delta)$$

Priors on all parameters were again set to be regularizing, but also somewhat informative based on likely ranges.

$$\alpha_\alpha \sim \mathcal{N}(0, 1)$$
$$\alpha_\beta \sim \mathcal{N}(-4, 1)$$
$$\alpha_\delta \sim \mathcal{N}(3, 1)$$
$$\tau_\alpha, \tau_\beta, \tau_\delta, \sim \text{Student}(3, 0, 1)$$

Lightly edited model results are shown below:

```
 Family: binomial
  Links: mu = identity
Formula: ArrsCCW | trials(ArrsTotal) ~ inv_logit(alpha)/(1 + exp(1 - inv_logit(beta)
                                       * (MonthNo + exp(delta))))
         alpha ~ 1 + t2(AgeMP, Sex, bs = c("tp", "re"), k = c(3, 3))
         beta ~ 1 + t2(AgeMP, Sex, bs = c("tp", "re"), k = c(3, 3))
         delta ~ 1 + t2(AgeMP, Sex, bs = c("tp", "re"), k = c(3, 3))
   Data: wy_demo_arrs[year(Month) < 2020, ] (Number of observations: 2856)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smooth Terms:
                    Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(alpha_t2AgeSex_1)   1.48      1.15     0.07     4.30 1.00      955     1056
sds(alpha_t2AgeSex_2)   3.51      1.71     1.31     8.16 1.01      868     1277
sds(beta_t2AgeSex_1)    0.81      0.69     0.04     2.49 1.00     1387     1162
sds(beta_t2AgeSex_2)    0.56      0.55     0.02     1.98 1.00     1124     1250
sds(delta_t2AgeSex_1)   0.66      0.58     0.03     2.25 1.00     1467     1017
sds(delta_t2AgeSex_2)   1.51      0.70     0.58     3.31 1.00     1064     1077
```

```
Population-Level Effects:
                Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
alpha_Intercept     1.22      0.63    -0.11     2.41 1.00     1223     1365
beta_Intercept     -4.41      0.26    -4.85    -3.81 1.00      856      888
delta_Intercept     5.27      0.31     4.51     5.80 1.00     1173      921

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
Warning message:
There were 5 divergent transitions after warmup. Increasing adapt_delta above
0.8 may help. See
http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
```

The form of this model is best seen with the data, in Figure 18. The most important thing to notice is that the home- and community-based services takeup rate for older demographics seems to lag younger demographics.

This is likely because older people arriving into Medicaid long-term care may have higher needs that might require nursing home care. The lower plateau and slower growth towards that plateau for older demographics —combined with the growing numbers of those older demographics —is the best explanation for why we project the percentage of Medicaid LTC members in home-based settings to stagnate at around 65%.

3.4. Exit models

Once members arrive into the system and are allocated to either CCW or Nursing Home settings, enrollment grows. But a certain number of people also leave each setting each month, due to death, moving out of state, or switching between CCW and Nursing home.

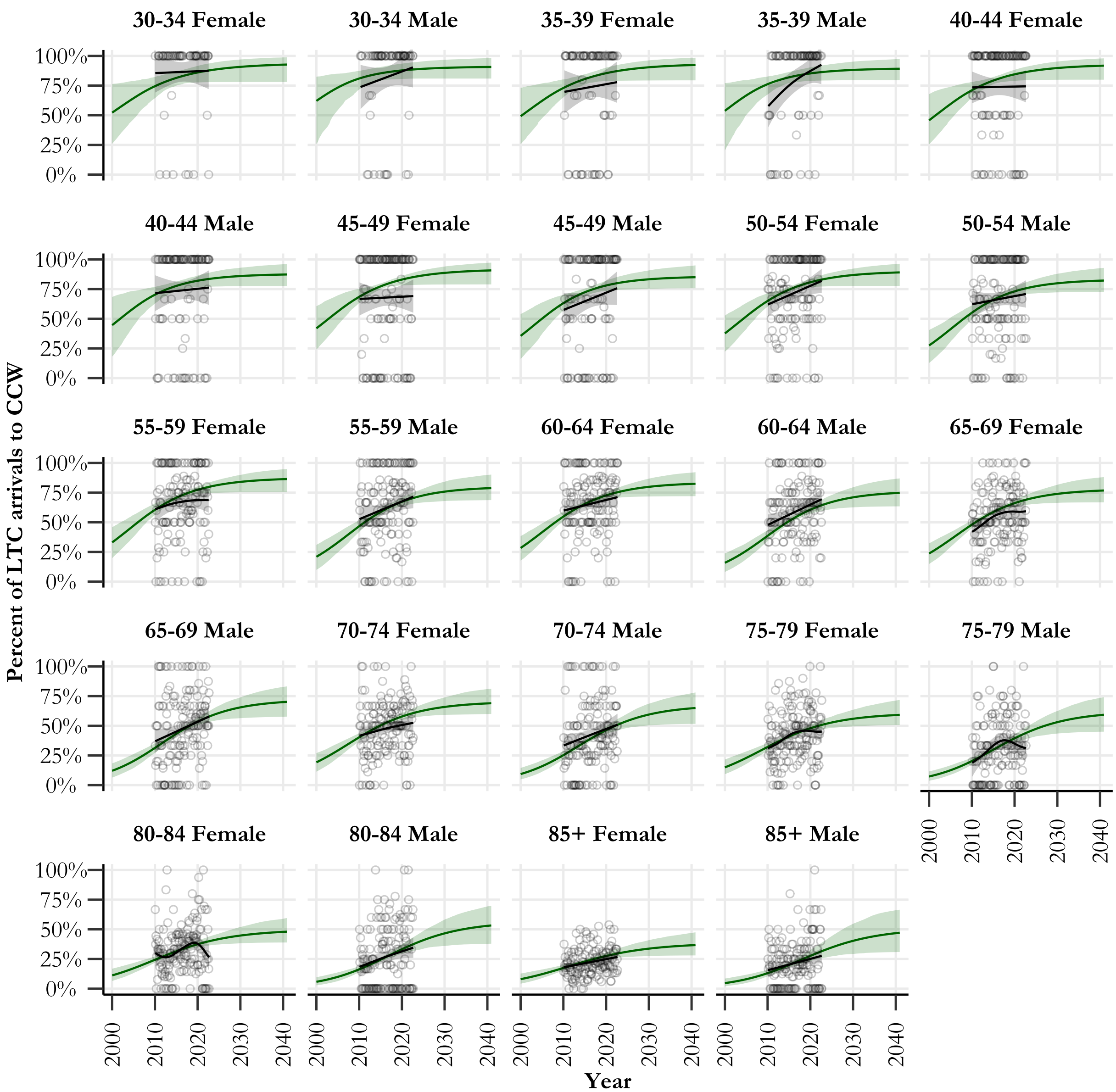
We model these exits roughly (i.e., not distinguishing between transitions between settings or demographics, as noted previously), for both nursing home and CCW. And, as with arrivals, we assume that pre-COVID trends in exit rates per enrollee will likely continue.

3.4.1. Nursing Home

We model exits for Nursing Home for month i and demographic group j using the same assumption of Poisson-distributed counts as arrivals, only this time the offset/exposure is Nursing Home enrollment, not underlying population.

And again similar to how we looked at arrivals, the rate parameter is modeled using a tensor product smooth of time (month number) and demographic group. We also add the same varying effects for the interaction of COVID and each demographic group, making the same assumption that this effect wears

Figure 18: Percent of arrivals going to CCW (green line and shading show the model, black lines and shading show a locally-estimated smoother



off in 2024.

$$
\begin{aligned}
&\text{NH Exits}_{ij} \sim \text{Poisson}\left(\lambda_{ij}\right) \\
&\quad \log(\lambda_{ij}) = \alpha + \alpha_{[\text{COVID}\times j]} + t2^{gp}_{re}(\text{Month No.}_i, j, \tau) + \text{offset}(\log(\text{NH Enrollment}_{ij}))
\end{aligned}
$$

Priors on parameters include:

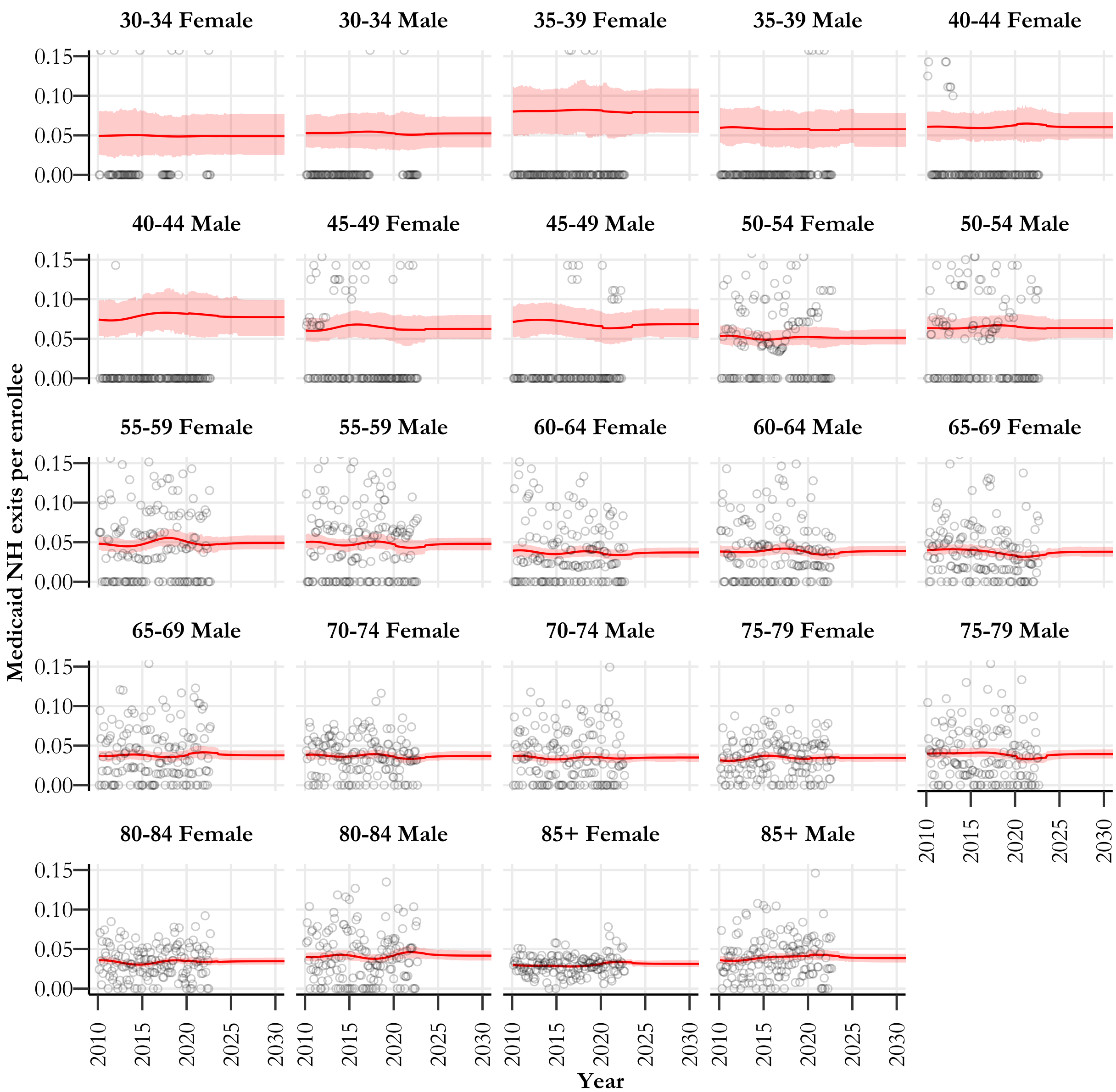
$$
\begin{aligned}
\alpha &\sim \mathcal{N}(0,1) \\
\tau &\sim \text{Student}(3,0,1) \\
\alpha_{[\text{COVID}\times j]} &\sim \text{Student}(3,0,2.7)
\end{aligned}
$$

Model output is shown below. Note that we use the same smooth specifications as the arrival model because of our assumptions that pre-COVID trends will continue throughout the projection period.

```
 Family: poisson
  Links: mu = log
Formula: ExitsNH ~ 1 + (1 | COVID:DemoGroup) + t2(MonthNo, DemoGroup,
                                                      bs = c("gp", "re"),
                                                      m = list(c(-3, 12), NA))
                   + offset(log(EnrollmentNH))
   Data: nh_model[EnrollmentNH > 0, ] (Number of observations: 3461)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smooth Terms:
                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(t2MonthNoDemo_1)     0.27      0.07     0.13     0.42 1.01      394      644
sds(t2MonthNoDemo_2)     1.51      0.28     1.06     2.13 1.01      436      812

Group-Level Effects:
~COVID:DemoGroup (Number of levels: 48)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.06      0.04     0.00     0.15 1.01      342      533

Population-Level Effects:
          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept    -3.06      0.07    -3.19    -2.93 1.02      341      788

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
Warning message:
There were 4 divergent transitions after warmup. Increasing adapt_delta above
0.8 may help. See
http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
```

The fitted exit rates for nursing home are shown with the observed rates (exits/enrollment) in Figure 19.

Figure 19: Nursing home exits



3.4.2. Community Choices Waiver (CCW)

This exit model is identical to the Nursing Home model; we just use exits from the CCW as the outcome and CCW enrollment as the offset/exposure.

$$
\begin{aligned}
\text{CCW Exits}_{ij} &\sim \text{Poisson}\left(\lambda_{ij}\right) \\
\log(\lambda_{ij}) &= \alpha + \alpha_{[\text{COVID}\times j]} + t2^{gp}_{re}(\text{Month No.}_{i}, j, \tau) + \text{offset}(\log(\text{CCW Enrollment}_{ij})) \\
\alpha &\sim \mathcal{N}(0, 1) \\
\tau &\sim \text{Student}(3, 0, 1) \\
\alpha_{[\text{COVID}\times j]} &\sim \text{Student}(3, 0, 2.5)
\end{aligned}
$$

The model output is shown below.

```
 Family: poisson
  Links: mu = log
Formula: ExitsCCW ~ 1 + (1 | COVID:DemoGroup) + t2(MonthNo, DemoGroup,
                                                  bs = c("gp", "re"),
                                                  m = list(c(-3, 12), NA))
                      + offset(log(EnrollmentCCW))
   Data: nh_model[EnrollmentCCW > 0, ] (Number of observations: 3624)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smooth Terms:
                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(t2MonthNoDemo_1)     0.48      0.08     0.34     0.65 1.00      501      933
sds(t2MonthNoDemo_2)     0.61      0.30     0.07     1.19 1.02      319      658

Group-Level Effects:
~COVID:DemoGroup (Number of levels: 48)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.09      0.05     0.01     0.19 1.01      268      560

Population-Level Effects:
          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept    -3.75      0.04    -3.83    -3.67 1.00     1142     1110

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
Warning message:
There were 6 divergent transitions after warmup.
Increasing adapt_delta above 0.8 may help.
See http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
```

As with the nursing home exit model, Figure 20 shows how the fitted rate compares with observed rates.

Figure 20: CCW home exits