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Mark Gordon
Governor

MEMORANDUM

Date: January 10, 2023

To: Joint Labor, Health and Social Services Committee
Joint Revenue Committee
Joint Appropriations Committee

From: Stefan Johansson, Director
Wyoming Department of Health

Subject: 2023 Medicaid Expansion Estimates

Ref: J-2023-118

Each year, the Department of Health updates its projections of potential enrollment and cost under various Medicaid expansion scenarios, with the objective of providing the Governor and lawmakers the best possible foundation on which to make their decisions.

Please find this year's projection attached.

SJ/FF/jg

c: Governor Mark Gordon
Legislative Service Office (electronic copy)
State Department Depository (electronic copy)

MEDICAID EXPANSION IN WYOMING

ENROLLMENT AND COST PROJECTIONS

Wyoming Department of Health
January 10th, 2023

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Executive Summary

If Wyoming were to expand Medicaid to non-disabled childless adults under 138% of the Federal Poverty Level (FPL) per the Patient Protection and Affordable Care Act ("the ACA"), the Department of Health would recommend **an initial biennial appropriation of $22 million in State General Funds and $177 million in Federal Funds.** If the $54 million incentive from the 2021 American Rescue Plan Act ("ARPA") is considered, there would be a **net ~ $32 million of State General Fund savings** to the State in this first biennium, which could likely cover the costs of expansion for a second biennium. There are some important caveats to note:

- The estimate comes with significant uncertainty. For State Funds, we are 90% sure the required appropriation will be $17 - $26 million over the first two-year period;
- The model assumes an enrollment growth curve that begins at ~ 5,000 people and continues to grow well past two years; subsequent biennial appropriations will necessarily be larger than this estimate.
- It assumes a "vanilla" expansion of Medicaid, without the kind of plan design bells and whistles (e.g., premiums, work requirements) that would require a waiver of the Social Security Act.
- We have not updated our expansion model from last year, due to the temporary effects of the Public Health Emergency on nationwide Medicaid enrollment trends.

Aside from the appropriation estimate, the highlights from this analysis include:

- We anticipate enrolling ~19,000 new Medicaid members by the end of the first biennium. This figure is close to the original (2011) Milliman estimate, but we project both a wider range of uncertainty — with 90% of scenarios falling between 12,000 and 27,000 people at the 24-month mark — and note that the 24-month estimate is only part of a larger enrollment trajectory.
- Of those enrolling, ~ 60% of individuals will have incomes in the insurance coverage gap (100% FPL or less); ~ 55% will have previously been uninsured, and ~ 56% will be employed.
- The estimated impacts of Medicaid expansion on newly-enrolled members include: a slight decrease in mortality for uninsured individuals between 45 and 64, increased healthcare utilization, improved mental health, and increased financial stability.
- Two significant second-order effects of expansion come from the "crowding-out" of private insurance coverage (i.e., previously insured members moving to Medicaid). These include:
    - Non-trivial (~50-67%) dampening of projected revenues to providers due to Medicaid rates being lower than commercial rates, though net provider revenue will almost certainly increase.
    - A probable 5 to 15% decrease in average per-person costs for members remaining on the Exchange, which would be similar to the implementation of a high-risk pool.

BACKGROUND - TRADITIONAL MEDICAID

This background section provide a high-level overview of the overall Wyoming Medicaid program before describing the specific circumstances around the idea of Medicaid expansion itself.

What is Medicaid?

Medicaid is a **joint Federal-State social insurance program** that pays for the **medical** and **long-term care** of **low-income and medically-needy individuals and families**. Table 1, below, illustrates the range of services that Medicaid pays for.

Table 1: General overview of Medicaid services (not inclusive)

Service type	Examples
Medical care	▪ Physician and other provider office visits ▪ Outpatient and inpatient hospital services ▪ Prescription drugs ▪ Behavioral health
Extended medical benefits	▪ Dental ▪ Vision
Long-term care	▪ Facility-based / institutional services ▪ In-home services ("Home and Community-based Waivers")
Other	▪ Non-emergency transportation ▪ Screenings and treatment referrals ▪ Cost-sharing for **Medicare** medical services for certain members.

Medicaid eligibility is limited

Having a low income by itself **does not** automatically qualify you for Medicaid in Wyoming. While most people on Medicaid are indeed low-income, people must also fall into certain **categories** based on age or physical health status. These categories include, but are not limited to, those in Table 2, below, which breaks down average monthly enrollment in SFY 2022 for the largest eligibility groups.

Table 2: SFY 2022 largest Medicaid eligibility categories by enrollment (~93% of total enrollment)

Eligibility category	Average enrollment
Low-income children	39,135
Very low-income family caretakers	9,831
On Supplemental Security Income (SSI)	5,908
Long term care - elderly and physically disabled	3,816
Individuals with intellectual/developmental disabilities	2,502
Pregnant women	3,461

Medi<u>CAID</u> is not Medi<u>CARE</u>

Medicare is an **entirely federal health insurance program** that pays most medical costs (and some short-term home- and facility-based long-term care costs) for individuals age 65 and older and certain disabled individuals under age 65.

The idea of Medicare developed between 1945 and 1965 as a way to provide health insurance to older Americans, who, due to the underwriting of their age and medical conditions, had difficulty obtaining insurance on the private market.[1] This was a relatively new problem, since health insurance only became widespread after medicine was purged of (most) quackery[2] and began to prove more useful to society in the early 20th century.

Medicare is a collection of four different benefit plans:

- **Part A** pays for approximately 80% of hospital and *short-term* nursing home and home-health services. Because of the absence of an out-of-pocket maximum for the ~ 20% of cost sharing in Part A, many beneficiaries also purchase private "MediGap" policies to cover this risk.

- **Part B**, which is optional, covers medically-necessary office and outpatient services from physicians and other practitioners.

- **Part C**, also known as "Medicare Advantage", is an option for enrollees to replace "traditional Medicare" (Parts A and B) with enrollment in a privately-operated managed care plan.

- **Part D**, available since 2006, covers prescription drugs through private plans operated by insurers and pharmacy benefit managers.

Medicare funding comes from a mix of sources — Medicare payroll taxes (36%), beneficiary premiums (15%) and federal general revenues (43%). Medicaid, on the other hand, is funded through a combination of federal general revenues and State funds.

Despite Medicaid and Medicare being distinct programs, many low-income older people can be on both programs at the same time. For these "dual-eligibles", Medicaid acts as a supplemental 'MediGap' policy, covering much of the patient cost sharing, as well as member premiums.

Medicaid's history is part of the long history of 'poor relief' programs

Unlike Medicare, the roots of Medicaid have more in common with other means-tested programs like food stamps or welfare, and go back to the systems of "indoor" and "outdoor relief" formalized by the Elizabethan Poor Laws (1597 - 1601), as adopted in the American Colonies. These kinds of

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[1] In the 1960s, 56% of Americans over 65 were not covered by health insurance.

[2] Flexner, Abraham. "Medical Education in the United States and Canada. A report to the Carnegie Foundation for the Advancement of Teaching. 1910.

local- and county-level poor relief programs were greatly expanded after the Great Depression, and increasingly centralized under State and Federal governments in the 1960s and 1970s.

Today's Skilled Nursing Facilities (SNFs), for example, are the current incarnation of what were called "rest homes" in the 1950s, which, in turn, evolved out of the "board and care homes" that gradually replaced the county and parish "almshouses" of the 18th and 19th centuries. These changes followed governmental funding policies. In the 1940s and 50s, for example, nursing homes began to be paid primarily through state and federal "medical vendor" programs; these were supplanted in the early 1960s by the Kerr-Mills "Medical Assistance to the Aged" program, which formed the base for Medicaid five years later.

Medicaid, as we know it today, was officially created as a voluntary State-Federal partnership in 1965 with addition of Title XIX to the Social Security Act. Wyoming began participating in July of 1967 with the passage of Senate File 183. Arizona was the last state in the Union to join Medicaid, in October of 1982.

State administration, federal oversight

Medicaid is administered by states per agreements), known as a "State Plans," with the federal Centers for Medicare and Medicaid Services (CMS). Any changes to each State Plan must be approved by CMS, but states do have significant leeway in operating their programs between certain guardrails.

Federal matching funds are significant

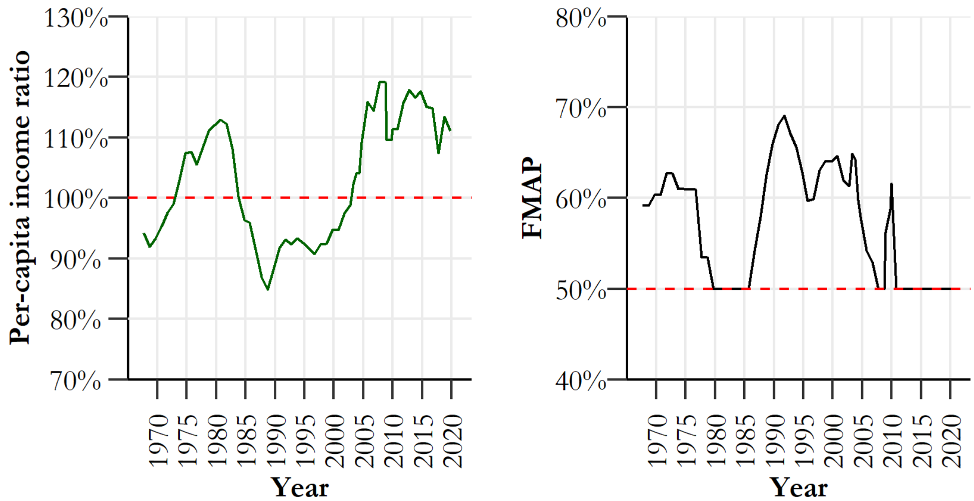
The federal government reimburses states a significant fraction of their Medicaid expenditures, known as the "Federal Matching Assistance Percentage" (FMAP). The match varies by state and over time, but is set by formula in proportion to the state's per-capita personal income relative to the national per-capita personal income. The formula, as established in the Social Security Act, is:

$$\mathrm{FMAP}_{\mathrm{State}} = 1 - \left(\frac{\text{Per capital income}^2_{\mathrm{State}}}{\text{Per capital income}^2_{\mathrm{US}}} \times 0.45 \right)$$

For Wyoming, the FMAP we have received over the last decade has generally been around the statutory floor of 50% (with the exception of a recent temporary bump in response to the COVID-19 pandemic). Poorer states like Mississippi and West Virginia have FMAPs as high as 77%.

The history of Wyoming's FMAP is shown in Figure 1, on the next page, along with the ratio of our per-capita personal income to the national figure. Although there has been a recent temporary increase to Wyoming's FMAP in response to the COVID Public Health Emergency (PHE), previous trends indicate that Wyoming's traditional FMAP will remain at the 50% floor for the foreseeable future.

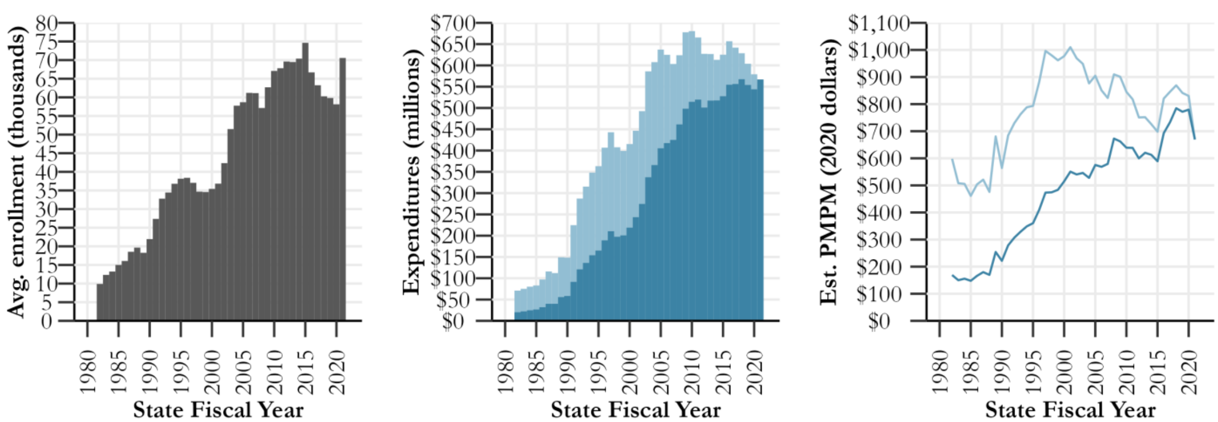
Figure 1: History of Wyoming's per-capita personal income in relation to the national figure (left), and how this has affected our Federal Match (right).



Expenditures and enrollment have increased significantly since the 1980s, but have been relatively stable over the last decade.

Figure 2, below, shows the historical trend in Wyoming Medicaid enrollment, expenditures, and per-member per-month (PMPM) costs. Expenditures and PMPM are also adjusted for inflation using the State and Local GDP Deflator.

Figure 2: Historical Wyoming Medicaid enrollment (left), expenditures (middle, with nominal expenditures in dark blue, inflation-adjusted 2021 dollars in light blue), and per-member per-month (PMPM) costs.



Because eligibility is partly tied to income, enrollment in Medicaid tends to increase in bad economic times and decrease when things improve. Complicating the picture in Wyoming, however, has been the implementation of a rules-based eligibility system in 2014 that significantly tightened up eligibility decisions.

Additionally, note the resulting steady decline in enrollment from 2015 to 2020, though enrollment has since trended up due to the (temporary) prohibition on States disenrolling members during the Public Health Emergency.

Trends in enrollment, expenditures, and per-member per-month (PMPM) costs over the last decade are shown specifically in Table 3, below:

Table 3: Medicaid expenditures, average monthly enrollment and per-member per-month (PMPM) costs, 2010 - 2021

SFY	Expenditures	Avg. Enroll	PMPM
2010	$514,529,323	68,484	$626
2011	$519,823,344	69,756	$621
2012	$510,857,708	69,561	$612
2013	$512,934,509	69,166	$618
2014	$513,535,575	70,386	$608
2015	$524,279,441	74,812	$584
2016	$556,565,588	67,907	$683
2017	$556,274,739	63,247	$689
2018	$567,478,640	60,263	$674
2019	$554,032,539	59,826	$771
2020	$543,792,374	58,130	$779
2021	$553,071,896	67,681	$681

BACKGROUND - MEDICAID EXPANSION

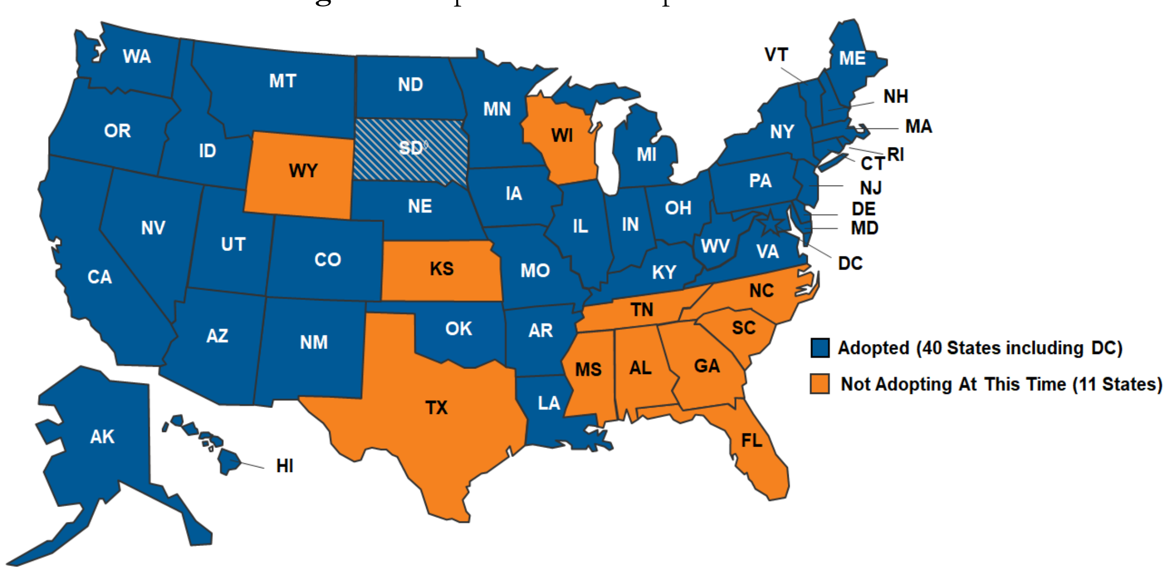
Medicaid expansion is an optional pathway to provide health insurance to low-income, childless adults, who otherwise have no access to affordable coverage.

The original idea of expanding Medicaid medical benefits to low-income adults was a component of the 2010 Patient Protection and Affordable Care Act ("the ACA"). This expansion was intended to act in concert with the private insurance provisions of the ACA to allow all individuals under 400% of the Federal Poverty Level (FPL) to acquire subsidized health insurance. The Supreme Court, however, ruled in 2012 (*National Federation of Independent Business v. Sebelius*) that a mandatory expansion of Medicaid would be unconstitutionally coercive on states. This effectively made Medicaid expansion an optional issue.

While optional, the incentives for States to expand are strong. Unlike the traditional federal match for Medicaid, the federal government will match expansion expenditures with 90% federal funds. In addition, Section 9814 of the 2021 American Rescue Plan Act (ARPA) sweetened incentives further by providing a temporary 8-quarter five percentage point (5%) increase in the Federal Medicaid Assistance Percentage (FMAP) for the State's *traditional* Medicaid clients. For Wyoming, we estimate the gross value of this incentive (i.e., excluding the costs of the expansion itself) to be worth ~ $54 million for one biennium.

Currently, 40 states (including DC) have elected to expand Medicaid; 11 have not, as shown on Figure 3, below. Note on the map that South Dakota has adopted expansion but not yet implemented it.

Figure 3: Map of Medicaid expansion states[3]



[3] Kaiser Family Foundation State Health Facts. https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/

The primary effect of this series of events has been the creation of a health insurance 'coverage gap' in the lowest-income group (0-100% of the Federal Poverty Level) between expansion and non-expansion states. Simply put, because the original ACA contemplated that all of these individuals would be covered by Medicaid, these individuals are simply not eligible for premium subsidies that begin at 100% FPL.

Table 4, below, illustrates this gap by showing what form of subsidized health insurance (Medicaid in purple, Exchanges in green) is available for a single, childless adult at various income levels in expansion states (right) and non-expansion states (left). The table also reflects the effect of subsidies provided under the American Rescue Plan Act (ARPA) of 2021, and extended to 2025 under the Inflation Reduction Act (IRA).

Table 4: Insurance coverage options for childless adults under ARPA/IRA: 2021 - 2025

Income range (percent of the Federal Poverty Level)	**Upper bound income for 2021** (single person)	**Coverage options**			
		Non-Medicaid Expansion states		**Medicaid Expansion states**	
		Premium subsidy	Cost-sharing subsidy	Premium subsidy	Cost-sharing subsidy
0 - 100%	$12,880	No subsidy available		Medicaid - low to no premiums	Medicaid - low cost-sharing (plan covers >97% of average medical costs)
101 - 138%	$17,774	Benchmark premium less 0% of income.	Plan covers 94% of average medical costs.		
139 - 150%	$19,320	Benchmark premium less 0% of income	Plan covers 94% of average medical costs.	Benchmark premium less 0% of income.	Plan covers 94% of average medical costs.
151 - 200%	$25,760	Benchmark premium less 2% of income	Plan covers 87% of average medical costs.	Benchmark premium less 2% of income.	Plan covers 87% of average medical costs.
201 - 250%	$32,200	Benchmark premium less 4% of income	Plan covers 73% of average medical costs.	Benchmark premium less 4% of income.	Plan covers 73% of average medical costs.
250 - 300%	$38,640	Benchmark premium less 6% of income	No cost-sharing subsidy, multiple plans available in various levels of generosity (metal levels)	Benchmark premium less 6% of income	No cost-sharing subsidy, multiple plans available in various levels of generosity (metal levels)
300 - 400%	$51,520	Benchmark premium less 8.5% of income.		Benchmark premium less 8.5% of income.	
400% +					

MODELING APPROACH

When Medicaid expansion first became a policy issue for States in 2011, the actuarial firm Milliman estimated that ~17,600 people would be covered by expansion. So why revise Wyoming's original projections?

The simple answer is that experience from other expansion states has shown that actual enrollment often exceeded original projections. This gap — between original projections[4] and actual enrollment[5] — is shown in Figure 4, below. Accordingly, we have updated our estimates, in house and each year since 2014, based on statistical models that incorporate the wide-ranging actual experiences of other states as well as the important variables specific to Wyoming.

Figure 4: Gap between projected and actual enrollment, by state. Dark blue bars show actual enrollment, and light blue bars show original projections.

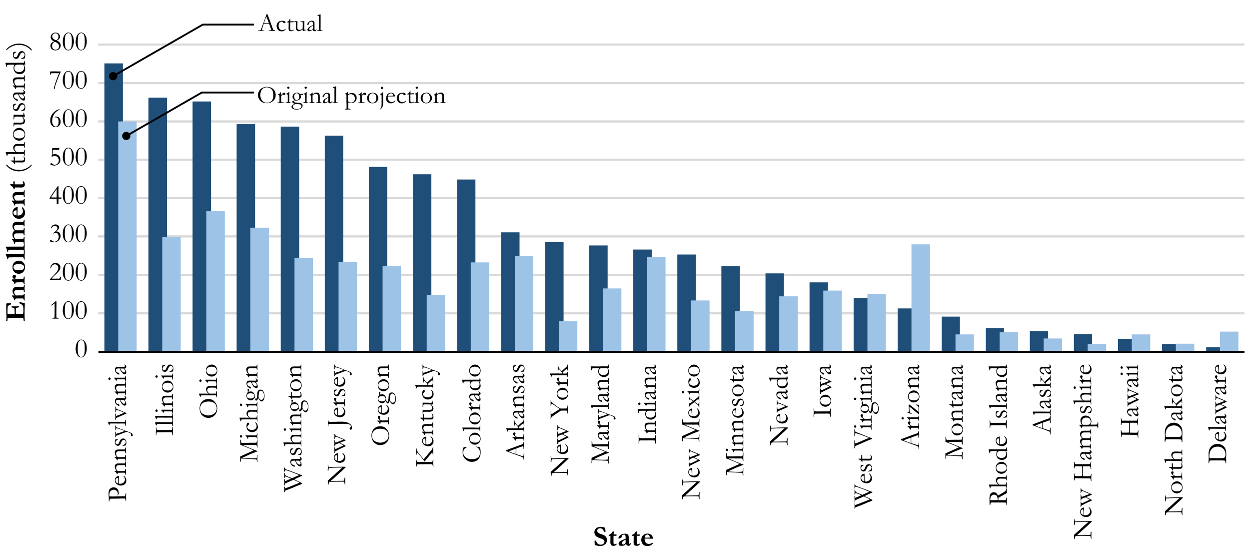


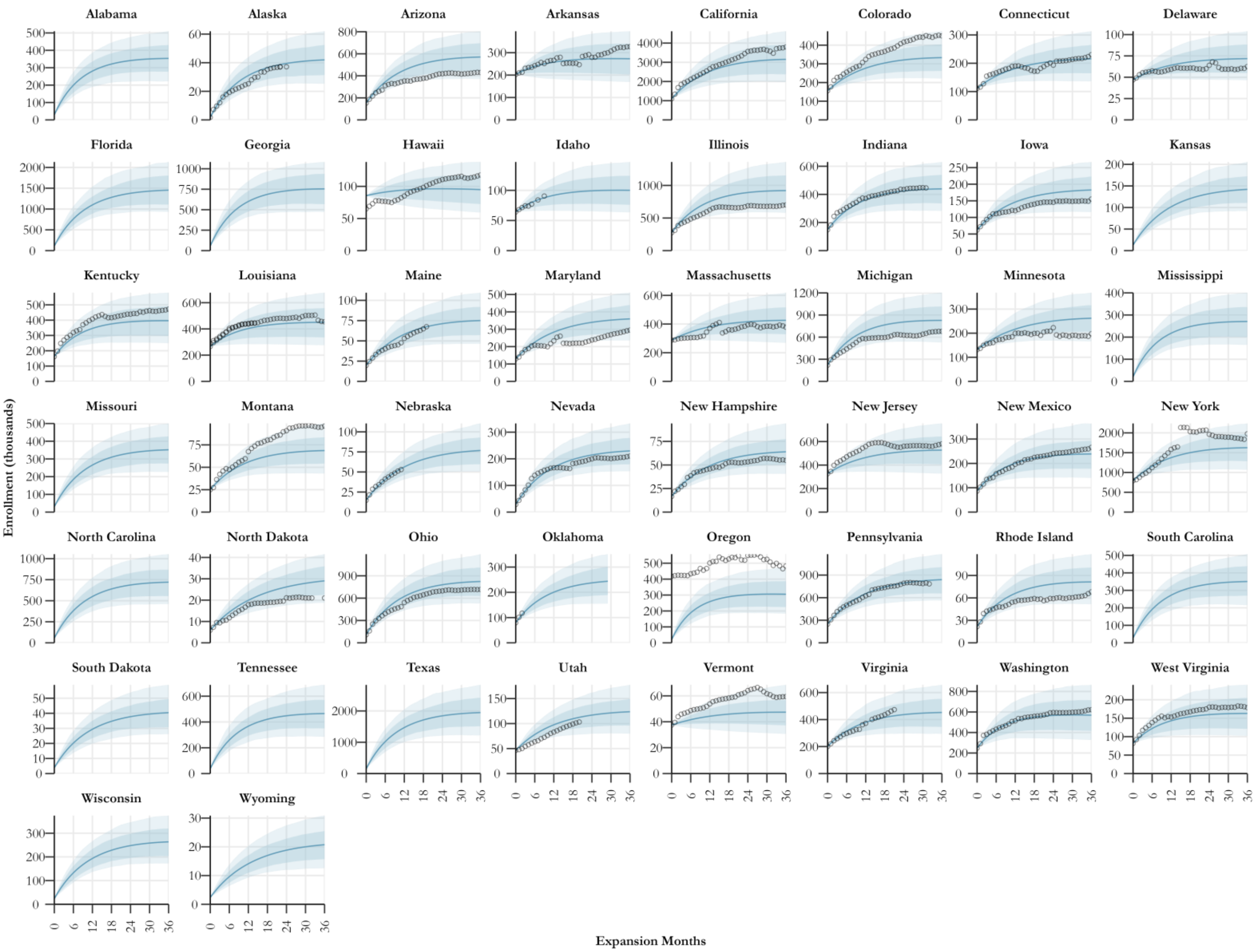
Figure 4 clearly demonstrates the need to thoroughly revise Wyoming's estimates of enrollment and costs, since many of the models used to estimate enrollment in these states may have been from the same consultants. We revise these estimates using two important principals:

- Projections should either be based on (a) empirical data or (b) fully-explained assumptions grounded in economic theory.
- Modeling and quantifying uncertainty is just as important as making point estimates.

[4] Projections collected by the AP, available here: https://www.washingtontimes.com/news/2015/jul/19/projected-actual-enrollment-for-medicaid-expansion/
[5] https://www.kff.org/health-reform/state-indicator/medicaid-expansion-enrollment

As a result, our current estimates are built off a statistical model that estimates overall enrollment *trajectories* for all states. Figure 5, below, shows how this model (blue lines and shaded regions) fits the actual experience for expansion states (black circles) and predicts the experience of non-expansion states.

Figure 5: Actual (black circles) vs. predicted (blue line) enrollment trajectories and uncertainty (blue shaded cones) for all states.



The Department has been refining these estimates since 2014, as more enrollment experience becomes available. This year, however, as enrollment trajectories were 'contaminated' by the effects of the Public Health Emergency and its prohibition on disenrollment, we have not updated our models.

Before 2022, the last version of these estimates was released in December 2020; at that point, we estimated expansion would cover an estimated 24,000 people and cost the State approximately $20 million in State General Funds in the first biennium. The models and data in this document incorporate several refinements:

- We updated enrollment counts for later expansion states (Montana, Idaho, Utah, Virginia and Maine), as well as included initial data for the latest expansion states (Nebraska and Oklahoma) in the enrollment model. We dropped Oregon and Hawaii from the model due to their unconventional trajectories. Note the poor model fit to these two states.

- We updated State-level predictors for the enrollment model to include results from the 2020 election. We also included two connected networks of states in the model; one based on physical geography (e.g., Wyoming is connected to Montana, Idaho, Colorado, etc.) and one based on a 'map' of similar states created by applying multidimensional scaling techniques to America's Health Ranking data.

- Our chronic disease model was updated to translate estimated self-reported conditions (e.g. diabetes, COPD, joint disease, etc.) into diagnosed conditions; i.e., conditions visible in Medicaid claims data.

- We also re-fit the claims model on updated Medicaid data for Family Care Adults between 2018 and 2020. The PMPM for this population increased from ~ $436 in SFY 2015 to ~$520 in SFY 2020. One of the largest cost drivers here was in prescription drugs, which more than doubled from ~$70 to ~$150 over the same time period.[6]

- For the first time, we included the offsetting effect of pharmacy rebates, since they are a growing factor in drug spending. Net of rebate, for example, our actual Medicaid pharmacy spending was 55% of gross spending in SFY2020.

- The overall administrative match rate was changed to 75%, since the marginal administrative costs of claims and eligibility processing for this group are matched at this higher rate.

Ultimately, these 2022 changes resulted in some shifts from the 2020 projection:

- Our enrollment projection is lower (19,000 vs. 24,000) and with a tighter range than last year. Adding new state enrollment data and updating state-level predictors helped decrease uncertainty.

- The updated claims data model has resulted in higher per-member per-month (PMPM) projections than in past reports. The new ~$520 PMPM we estimate for month 24 is very close to the FY19 $6,615 national average per full-year equivalent expansion enrollee (~$550 PMPM), though it's unclear if the national figure includes the effects of pharmacy rebate.[7] Despite the lower predicted enrollment, the higher PMPM results in higher projected costs to the state over the biennium ($21 million in SGF vs. $20 million). The increase is attenuated somewhat by the addition of rebate and change to administrative match.

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[6] SFY 2020 Wyoming Medicaid PMPM report. These figures do not include pharmacy rebate, since rebate is collected in aggregate and can't yet be specifically attributed to specific claims.

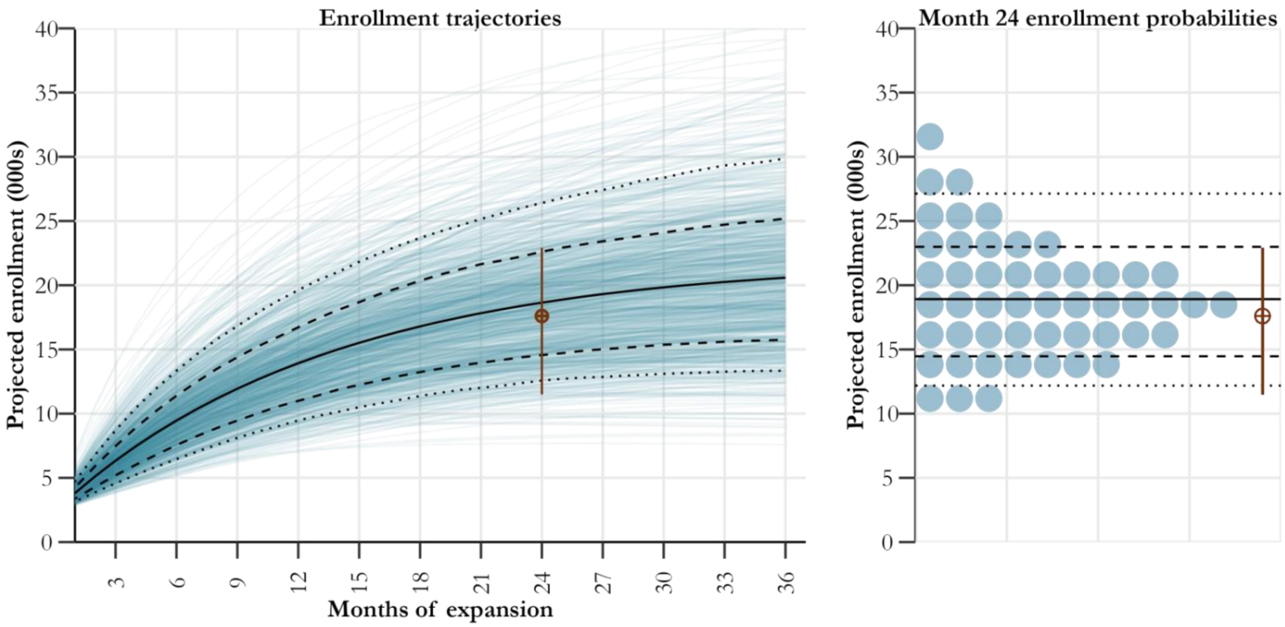
[7] https://www.macpac.gov/wp-content/uploads/2017/12/EXHIBIT-23.-Medicaid-Benefit-Spending-per-Full-Year-Equivalent-Enrollee-for-Newly-Eligible-Adult-and-All-Enrollees-by-State-FY-2019.pdf

Enrollment and Costs

Enrollment

After two years (24 months), we expect Medicaid expansion enrollment to reach approximately 19,000 people, though the count is projected to grow slightly over subsequent years before plateauing. Figure 6, below, shows the overall trajectories out to 36 months (left), as well as the range of uncertainty behind the enrollment 'slice' at 24 months (right).

Figure 6: Uncertainty in enrollment



On the figures, the dotplot[8] (right) and lines (left) show the range of potential scenarios resulting from the model. In order to quantify specific ranges, we annotate this figure with three sets of intervals:

- Dashed lines represent 67% percentile (equal-tailed) intervals. This means that, working in from the tails of the distribution, 67% of potential scenarios lie between the dashed lines. Dotted lines show 90% percentile intervals.

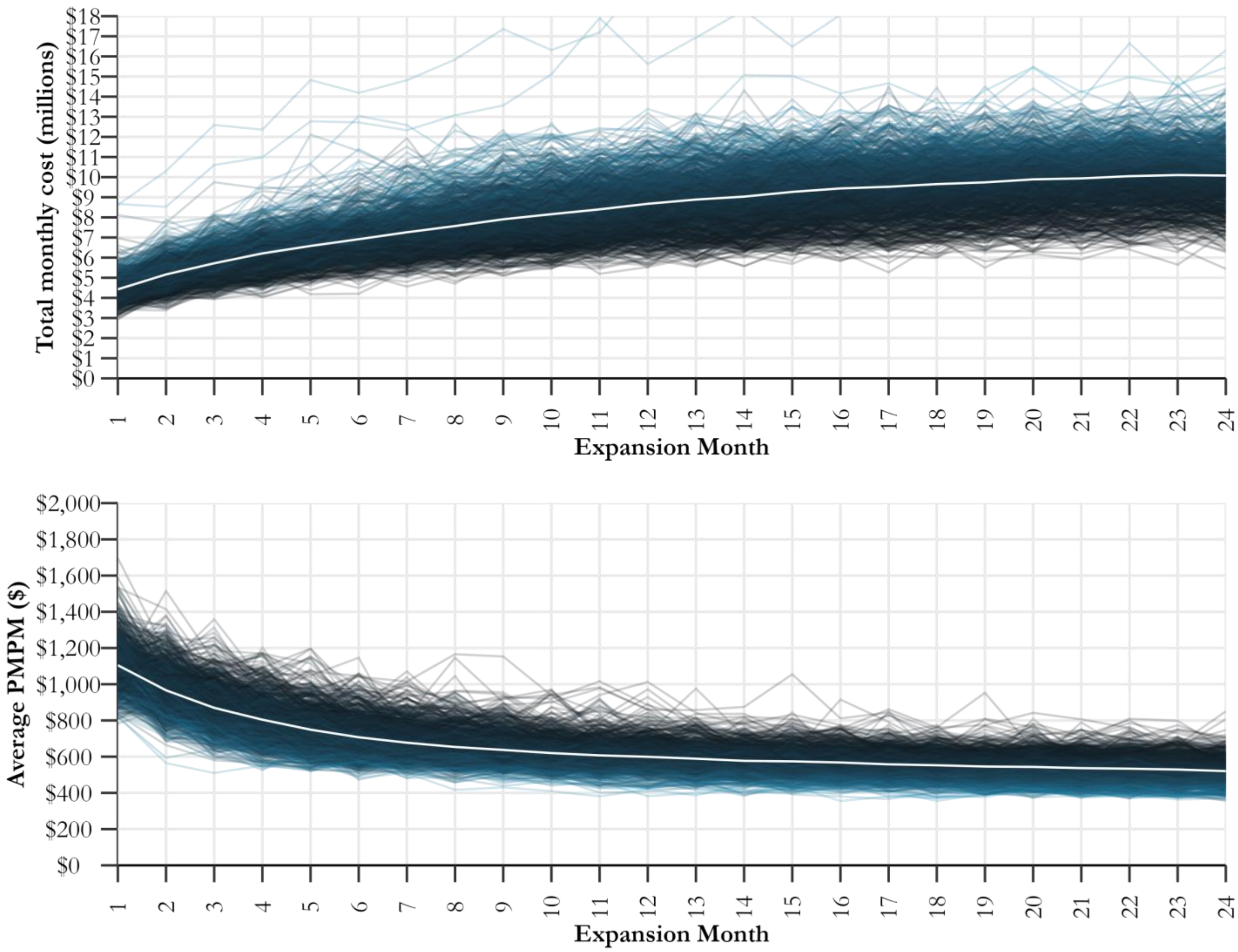
- The brown circle and lines show estimates from Milliman (2011) and their "high" and "low" scenarios. Our estimates are consistent with the original Milliman projections at 24 months, but note that the range of uncertainty is larger, and that we project a growth curve past the first biennium.

[8] There are a total of 50 dots here that represent probability, so counting dots and dividing by 50 will give you rough estimates. For example, the probability enrollment will be lower than 15,000 people in month 24 is represented by 10 dots out of 50 dots = 20%.

Costs
We project Medicaid medical and administrative costs for this population at ~$199 million for the first biennium. These costs will grow with a flatter trajectory than enrollment, due to the effects of adverse selection: our model assumes that the first people to sign up for Medicaid expansion will be the least healthy and thus the most expensive to cover.

This also means that, in the world of this model, enrollment has an inverse relationship with per-member per-month costs. In other words, if enrollment take-up is low, we anticipate the covered population to be sicker (and therefore more costly) than if take-up rate is high. Figure 7, below, shows the estimated trajectories for total monthly cost (upper panel) and per-member per-month medical costs (lower panel). Higher enrollment scenarios are shown as lighter shades of blue.

Figure 7: Projected monthly Medicaid expenditures (upper) and per-member per-month (PMPM) medical costs (lower). The white lines show expected values.

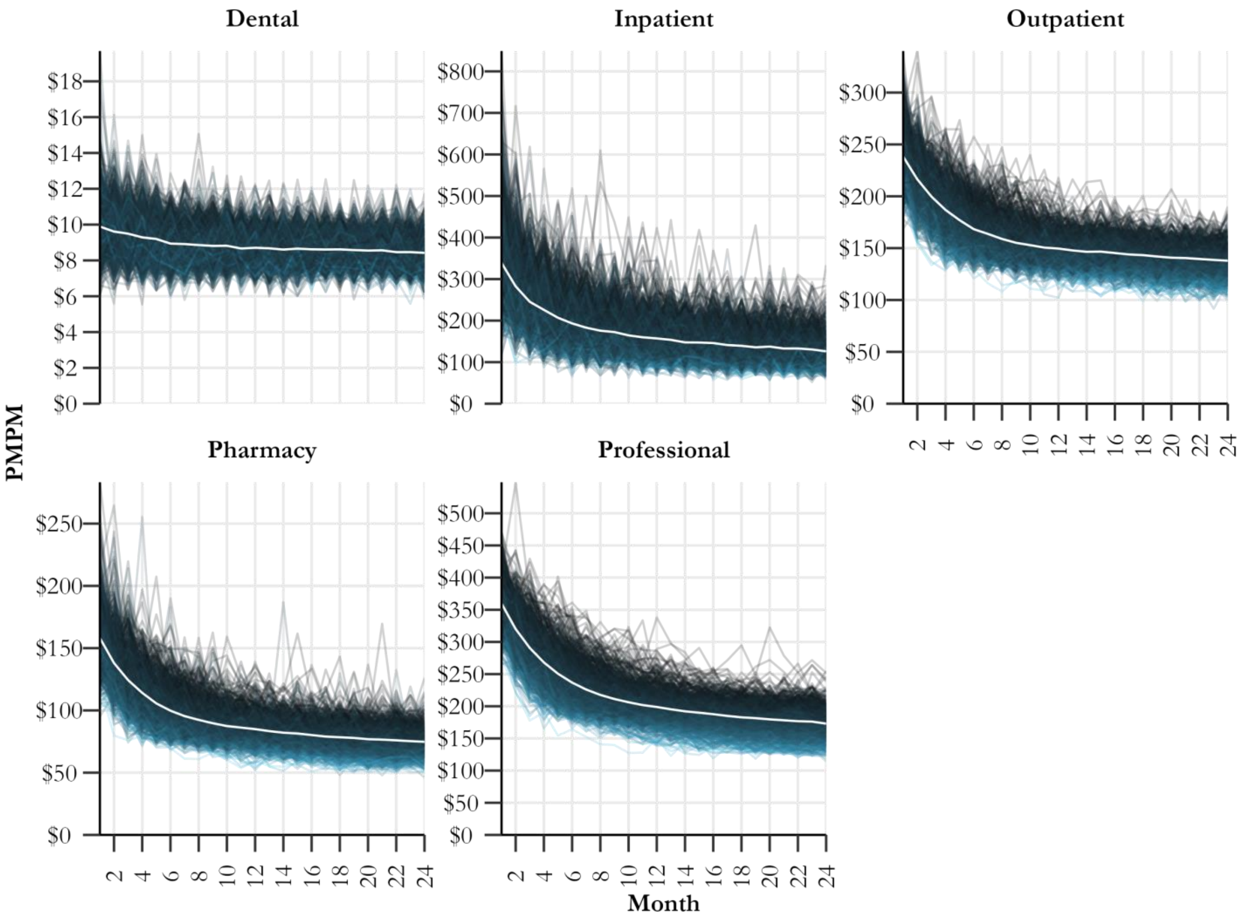


Note on the figure above that the expected total monthly costs at the end of the biennium are ~ $10 million. The State General Fund share would be between ~$1.1 [$0.8 - $1.3] million per month. With no other information, this is the figure we would use to project costs for the next biennium.

Per-member per-month costs

Breaking down per-member per-month (PMPM) costs by claim type in Figure 8, below, we see a similar correlation between enrollment and PMPM — scenarios with higher enrollment will likely have lower PMPM costs.

Figure 8: Modeled per-member per-month costs by service type. Blue lines represent scenarios where overall enrollment is higher. The white line shows the expectation across all scenarios.



Cost by provider category

When we combine expected expenditures by claim type with existing utilization patterns for low-income adults currently on Medicaid, we can estimate how many dollars will go to which kind of providers.

Table 5, on the next page, illustrates this breakdown of the total ~$199 million expected biennial cost. It tells us, for example, that we can expect in-state hospitals to receive ~$34.9 million in inpatient revenue and ~$24.8 million in outpatient revenue. Note, however, that crowd-out of private insurance (discussed in a subsequent section) will reduce potential revenue received by all providers, though net revenue will remain positive.

Table 5: Expected biennial expenditures by provider type and in-State vs. out-of-State location

Claim type	Expected biennial cost	Provider category	Percent of claim type[9]		Expected Expenditures	
			In-State	Out-of-State	In-State	Out-of-State
Dental	$2.77	Dental	96.6%	3.4%	$2.7	$0.1
Inpatient	$48.96	Hospital	71.3%	28.7%	$34.9	$14.1
Professional	$62.79	Ambulance	3.2%	0.4%	$2.0	$0.3
		Behavioral Health	19.2%	0.1%	$12.1	$0.1
		Dental	0.1%	0.0%	$0.1	$0.0
		Equipment / Supplies	3.2%	1.3%	$2.0	$0.8
		Laboratory/Imaging	4.2%	3.2%	$2.6	$2.0
		Other	11.4%	0.7%	$7.2	$0.4
		PT/OT	4.2%	0.1%	$2.6	$0.1
		Primary Care	17.8%	2.5%	$11.2	$1.6
		Specialist	24.6%	2.5%	$15.4	$1.6
		Vision	1.0%	0.2%	$0.6	$0.1
Outpatient	$47.72	Ambulatory Surgical Center	3.8%	0.1%	$1.8	$0.0
		Hospital	52.0%	4.4%	$24.8	$2.1
		Other	1.2%	0.4%	$0.6	$0.2
		PT/OT	0.1%	0.0%	$0.0	$0.0
		Primary Care	37.8%	0.3%	$18.0	$0.1
Pharmacy	$26.87	Pharmacy	83.1%	16.9%	$22.3	$4.5
Total medical	**$189.11**		**84.9%**	**15.0%**	**$179.3**	**$31.8**
Administrative	$9.46					
Total cost	$198.56					

Administrative costs

With a "vanilla" expansion (e.g., no waivers or other administrative overhead), we estimate administrative costs at 5% of total medical costs, which is consistent with the costs of the current Medicaid program. In any other scenario (e.g., waivers that change how Medicaid would administer the program or what benefits are offered), expected costs could increase.

Administrative costs are largely marginal — processing additional medical claims and eligibility applications generated by the new members. The State has the fixed infrastructure required to implement a "vanilla" expansion.

[9] These percentages come from existing Family Care (low-income Medicaid adult) utilization patterns.

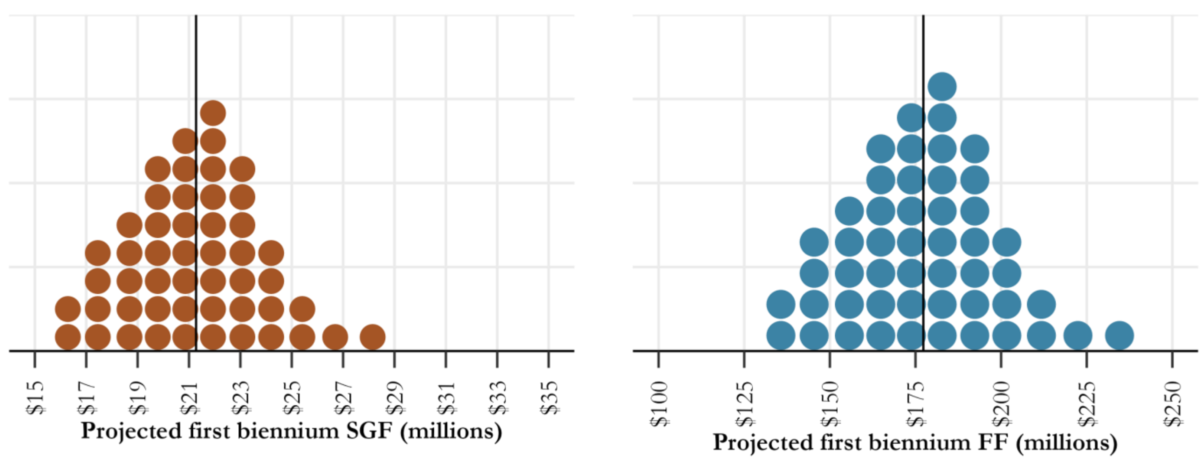
Required appropriation
In order to translate these total costs into a potential appropriation recommendation, we make some adjustments:

- Per the ACA, the Federal government will pay 90% of these medical costs after CY 2020. This only applies to a "vanilla" expansion. It's unclear what the matching percentage would be for a scenario under various Medicaid expansion waivers, but it could be lower than 90% depending on program elements and design.[10]

- The Federal government will match 75% of administrative expenditures.

Figure 9, below, shows the uncertainty in the State General Fund (SGF) and Federal Fund (FF) required expenditures for the first biennium. As with the enrollment slice, these are shown as dotplots, with 50 dots in each figure allocating the estimated probability across the x-axis.

Figure 9: Uncertainty in first biennium expenditures, by source



The uncertainty here is important. Our recommendation of $22 million SGF is based on the expected value ($21.3), but there is some non-negligible probability that actual SGF expenditures could be as high as $28 million (1 / 50 dots, or ~ 2%) or as low as $17 million (2 / 50 dots, or ~ 4%).

[10] FMAP for Wyoming has, in recent years, been at 50%.

Enrollee Profile

Because the simulation for enrollment and costs is based around Census data, we can take the simulation results and put together a profile of enrollees based on available demographic data.

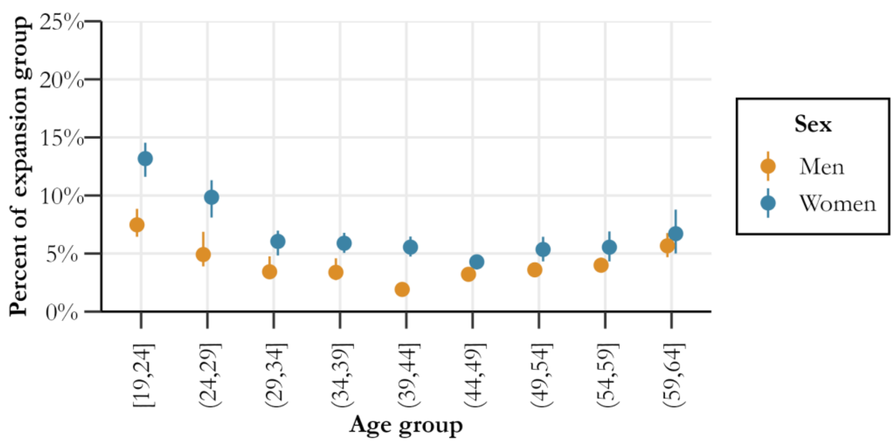
Demographics

In terms of age and sex, we characterize the Medicaid expansion population as having two broad groups:

- A group of younger (< 35 years old) people, making up an estimated 45% (40 - 49%) of the total enrollees. This population will largely (~60%) be female.
- An older (over 50 years old) group of enrollees, making up an estimated 30% (26 - 35%) of the expansion group.

This bimodal distribution can be seen in Figure 10, below, where orange dots and ranges show estimates for men and blue dots and ranges show estimates for women.

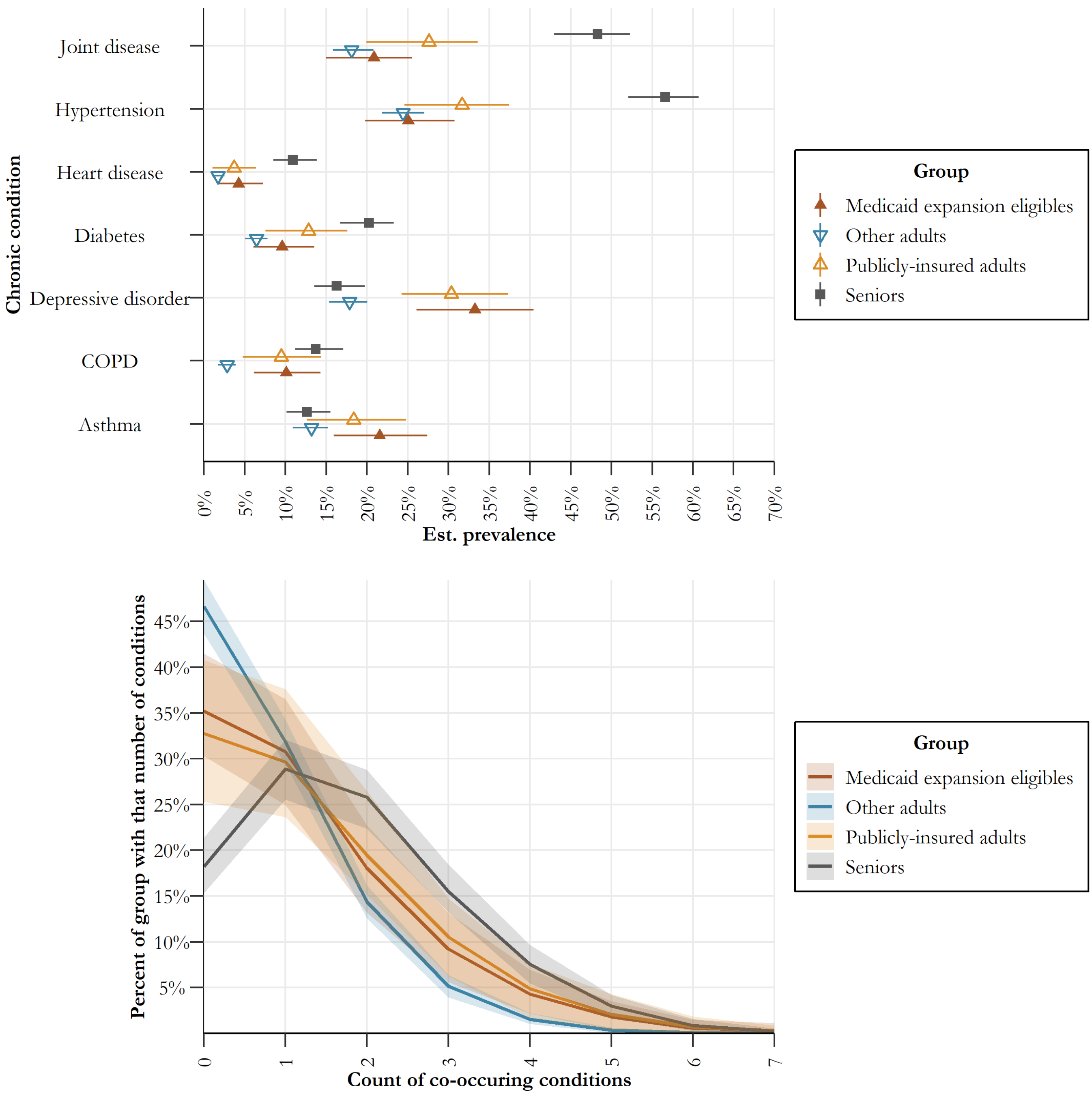
Figure 10: Age and sex estimates



Health status

Looking at seven different chronic conditions, we estimate that the expansion eligible group will be roughly similar to those adults between 18 and 64 that are currently on Medicaid or Medicare ("publicly-insured"). Figure 11, on the next page, shows our estimate of prevalence for Wyoming adults in various categories, as well as the total number of co-occurring conditions.

Figure 11: Chronic conditions



These estimates, of course, are for the total eligible, not those actually enrolled. As previously noted, the overall health of the pool will likely be negatively correlated with its size; a larger pool will be, on average, healthier. Conversely, a low-enrollment scenario will likely be less healthy, and thus have the higher per-member per-month costs seen in the lower panel of Figure 6.

Race/Ethnicity

We project that ~79% of the expansion group will be White, ~13% will be Hispanic, ~ 3% American Indian, ~2% Asian, and ~1% Black.

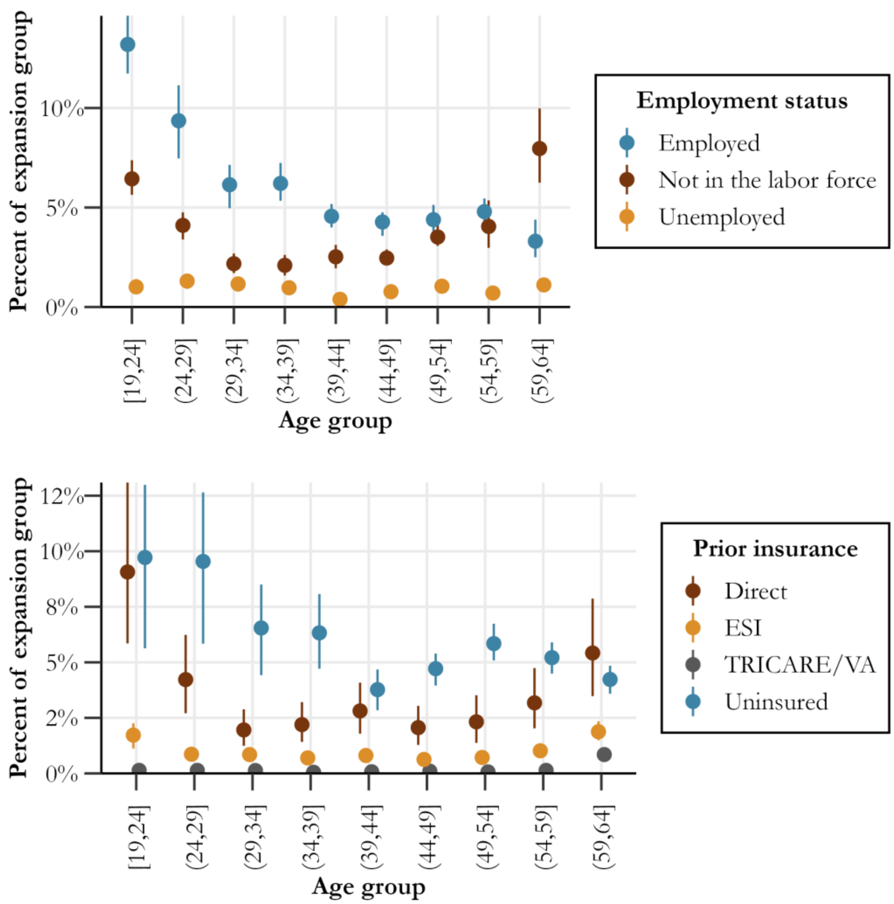
Education and income

We estimate that approximately 58% (55 - 61%) of enrollees will have incomes below 100% FPL; the remainder will be between 100 - 138% FPL. The vast majority of people will be high school graduates and most (~56%) will have at least some college education.

Employment and insurance coverage

Approximately 56% will be employed, 35% will not be in the labor force (e.g., retired or not looking for work), and 8% will be unemployed (and actively looking for work). Regarding insurance, we estimate that 56% (42 - 66%) of enrollees will have been previously uninsured, with the next largest fraction being the 33% (21 - 48%) that previously had directly-purchased insurance.

Figure 12: Estimated insurance and employment status by age group



Effects On Members

Aside from the obvious impact of expanding health insurance coverage and reducing the uninsured rate, many studies have attempted to estimate the effects of Medicaid expansion on newly-enrolled low-income individuals. The Kaiser Family Foundation maintains a good current summary of the literature.[11] Most of these studies, however, are observational and vary in quality and reliability.

Two studies are worthy of serious attention. Both come from quasi-experimental randomized controlled trials — the gold standard for any experiment, since they offer the best chance to estimate causal effects isolated from the problems of confounding variables.

(1) The first rigorous study was conducted in Oregon, which implemented a limited expansion of Medicaid in 2008, prior to the passage of the Affordable Care Act and the availability of the optional adult Medicaid expansion. The lottery-based design of the expansion afforded researchers a unique opportunity to conduct a randomized trial.

The following summary of effects comes from a dedicated web-page for the experiment, which can be accessed at https://www.nber.org/oregon/

(a) Health utilization generally increased, specifically in the following areas:

- Hospitalizations;
- Emergency department visits;
- Office visits;
- Prescriptions, particularly for mental health and diabetes; and,
- Preventive screenings - cholesterol monitoring and mammograms

(b) Financial hardship decreased. Medicaid members reported decreases in out-of-pocket spending, catastrophic medical expenditures, medical debt, and skipped bills.

(c) Self-reported health status increased and reported depression decreased, but physical health markers did not improve by any statistically-significant degree.

- Members on Medicaid had a 25% higher probability of reporting themselves in good to excellent health compared to the control group.

[11] https://www.kff.org/medicaid/report/the-effects-of-medicaid-expansion-under-the-aca-updated-findings-from-a-literature-review/ and https://www.kff.org/medicaid/report/building-on-the-evidence-base-studies-on-the-effects-of-medicaid-expansion-february-2020-to-march-2021/

- Rates of reported depression decreased by 9.2 percentage points compared to the control group baseline rate of 30 percent.
- No statistically-significant changes to blood pressure, cholesterol or glycated hemoglobin were detected.

(d) There was no statistically-significant evidence that Medicaid expansion changed employment status, earnings, or receipt of government cash benefits (e.g. TANF, SSI/SSDI).

- Researchers did note a small increase in SNAP ("food stamps") enrollment.

(2) The most recent study[12] took advantage of an IRS mailing in 2017 to 3.9 million randomly-selected individuals (out of 4.5 million) who had paid a tax penalty for lacking health insurance under the ACA. The objective of the mailing was to encourage people to enroll in coverage. As with the Oregon Health Insurance Experiment, this afforded researchers the opportunity to conduct a randomized study. On average, researchers found that each letter increased insurance coverage in this group by approximately 1 year for every 87 letters sent.

(a) The most important finding from this study, however, was the **estimated reduction in mortality for previously-uninsured 45-64 year-olds over the next two years by approximately 1 death for every 1,648 individuals who were sent the letter**. The study found no evidence of a reduction in mortality for younger age groups.

This study is groundbreaking in the sense that its size and quasi-experimental nature allowed researchers to rigorously estimate the effect of health insurance coverage on a relatively-rare outcome (death).

Application to Wyoming

If we assume the expansion of Medicaid in Wyoming has an effect analogous to this IRS mailing (i.e., it represents an intent-to-treat on the whole population of eligible people, not just those who enroll), this estimate would translate into **~ 2 - 4 avoided deaths** for the approximately 4,755 (+/-430) uninsured individuals between 45 and 64 in Wyoming below 138% FPL[13] over the next two years, **who would otherwise experience ~ 50 - 70 deaths** (an estimated baseline mortality rate of 1%) in the same period.

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[12] Goldin, Lurie and McCubbin. "Health Insurance and Mortality: Experimental Evidence from Taxpayer Outreach". NBER working paper No. 26533. http://papers.nber.org/tmp/91050-w26533.pdf

[13] American Community Survey 2019 5-year PUMS.

EFFECTS ON PROVIDERS

At first blush, Medicaid expansion would seem to be a pure benefit to medical providers in Wyoming. After all, if many previously-uninsured people are now covered by Medicaid, hospitals and physicians will see a decline in uncompensated care and bad debt, which will no doubt increase revenue (i.e., per Table 5 in the Costs section.)

Medicaid expansion will indeed reduce uncompensated care, but the actual revenue situation for providers is not so clear-cut. While we believe **net** revenues will ultimately increase, they will also be lower than total new revenue might suggest, due to the effect of "crowd-out" on private insurance.

What is crowd-out?
Many members who might be eligible for Medicaid expansion are currently covered by federally-subsidized private insurance purchased directly from the ACA Exchange.

- Here, premium subsidies (Advanced Premium Tax Credits, or APTCs) are generally available to individuals over 100% of the Federal Poverty Level (FPL), and cost sharing reduction (CSR) subsidies are generally available between 100 - 250% FPL.[14]

- Both of these subsidies make acquiring and using directly-purchased insurance fairly affordable for these income brackets.

- This situation should be contrasted with that of individuals below 100% FPL, **who get absolutely nothing** per the current Affordable Care Act.

"Crowd-out" means that the individuals between 100% and 138% FPL who are currently on the Exchange would almost certainly drop their private plans and enroll in Medicaid. This is for three reasons:

- These individuals have already demonstrated a need for health insurance.

- Depending on plan design, Medicaid will generally be more affordable than even these highly-subsidized plans.

- Most importantly, when individuals attempt to re-enroll on the Exchange during open enrollment season, they will be administratively re-directed to enroll in Medicaid.

[14] While the federal government has stopped paying insurers Cost Sharing Reduction subsidies, they still mandate the availability of low cost-sharing plans. In response, most insurers have significantly increased their premiums for Silver-level plans, dramatically increasing the revenue from Advance Premium Tax Credits. While this creates significant distortions between metal-level pricing, cost-sharing reduction subsidies are now effectively available from the APTC funding.

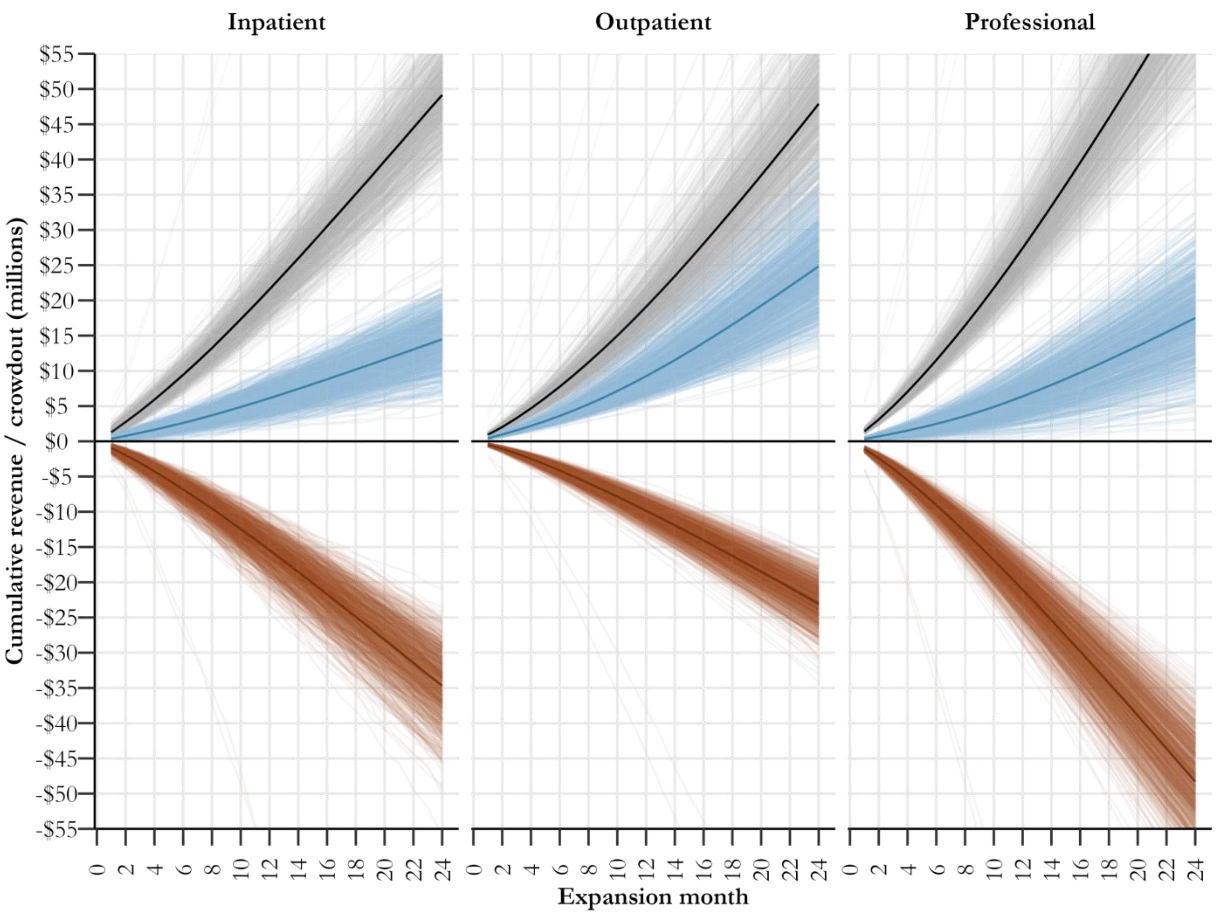
Some individuals covered by employer insurance will also move over to Medicaid, but this effect is less predictable (see the Methodology section for details on how crowd-out was implemented here).

Effect on provider revenues

Generally, private insurance pays higher unit prices than Medicaid. This means that the same previously-insured individuals using the same amount of health care under Medicaid would translate into a revenue loss for their providers for those particular patients.[15]

Figure 13, below, illustrates the cumulative effect of new Medicaid revenues (in black) against the lost revenue due to crowd-out (brown), with the net revenue shown in blue. Note that in all scenarios, **net revenue is positive for providers despite crowd-out**.

Figure 13: New revenue (black), estimated crowd-out (brown), and net revenue (blue)



[15] It should be noted that these lower unit prices (along with the 10% State match) also translate into probable net savings for the Federal government, but this effect is harder to estimate and will not be discussed here. Nonetheless, it does explain much of the reluctance by the Federal government to agree to partial Medicaid expansions (e.g., under 100% FPL).

To estimate these effects, we applied an estimated Medicaid-to-commercial rate ratio to the inpatient, outpatient and professional costs[16] experienced by those who were previously directly-insured or covered by employer-sponsored insurance in the simulation.

Table 6: Estimated Medicaid-to-commercial rate ratios by claim type

Claim Type	Medicaid-Commercial Ratio	Methodology	Source
Professional	0.64	Weighted average of ratios for provider types where rates were known (behavioral health, laboratory, primary care, specialist, and vision).	Navigant 2018 Medicaid rate benchmarking report.
Outpatient	0.85	Weighted average of estimated hospital aggregate rate (with UPL) and estimated FQHC/RHC rates (higher than commercial).	Milliman hospital cost study; CHIP data on FQHC/RHC payments
Inpatient	0.69	Estimated hospital aggregate rate (with UPL)	Milliman hospital cost study

For each claim type, the weighted average was calculated using existing low-income adult Medicaid utilization (by expenditure), shown in Table 5 in the costs section.

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[16] We specifically exclude pharmacy costs since changes in unit rates (a) largely accrue to out-of-state pharmaceutical companies and (b) the effects are difficult to determine due to the complications in pharmacy pricing (rebates, pharmacy benefit managers, etc.).

EFFECTS ON PRIVATE INSURANCE

The major effect Medicaid expansion has on the private insurance market is a likely 5 - 15% reduction in Exchange pool costs. This effect is akin to that of a high-risk pool: if the sickest (and therefore, the most expensive) enrollees are moved over to Medicaid, costs *should* decrease for the rest of the private market.

The real question is: are the individuals moving from Exchange coverage to Medicaid truly sicker or more-expensive than the pool average? Available evidence indicates that they are.

- One national study estimated average cost reductions at approximately 11%[17]; the same authors more recently estimated the impact on private insurance rates if Wisconsin were to expand Medicaid at 13 - 19%.[18]

- An actuarial study of New Hampshire's Medicaid Expansion concluded that if the expansion group were removed from the Exchange, adjusted claims costs would decrease by 14%.[19]

- The Kaiser Family Foundation estimates that states that expanded Medicaid had lower aggregate risk scores on their Exchange than states that did not.[20]

Using a Census-based simulation similar to the Medicaid expansion methodology, but restricted to the population of directly-insured individuals in Wyoming[21], we also arrive at a similar estimate of reduction in modeled costs: ~10%, with a 95% credible interval between 5% and 15%.

In addition to this evidence, there are also intuitive reasons to believe that the Medicaid expansion members are likely sicker and more costly than average.

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[17] Sen and DeLeire. "How does expansion of public health insurance affect risk pools and premiums in the market for private health insurance? Evidence from Medicaid and the Affordable Care Act Marketplaces." Health Economics. July 30, 2018. https://onlinelibrary.wiley.com/doi/abs/10.1002/hec.3809 and previous work (2016) here: https://aspe.hhs.gov/system/files/pdf/206761/McaidExpMktplPrem.pdf

[18] Sen and DeLeire. "Medicaid Expansion in Wisconsin Would Lower Premiums For Those With Private Insurance." Health Affairs blog. June 6th, 2019. https://www.healthaffairs.org/do/10.1377/hblog20190605.87178/full/

[19] Gorman Actuarial. 2016 Actuarial Analysis of NH Premium Assistance Program. https://www.nh.gov/insurance/reports/documents/08-28-17-ga-nh-pap-analysis-final.pdf

[20] https://www.kff.org/health-reform/issue-brief/data-note-effect-of-state-decisions-on-state-risk-scores/

[21] In the simulation, we apply the BRFSS model (Model 2 in the Technical Details section) to estimate the count of chronic diseases for the subset of directly-insured individuals in the American Community Survey PUMs. We then apply a MEPS-based utilization model (Model 5, based on directly-insured individuals in that survey) to estimate standardized costs based on the predicted chronic disease count and demographic factors. Simulation results are used to estimate what happens to overall enrollment and pool average costs if individuals between19-64 and below 138% FPL are removed.

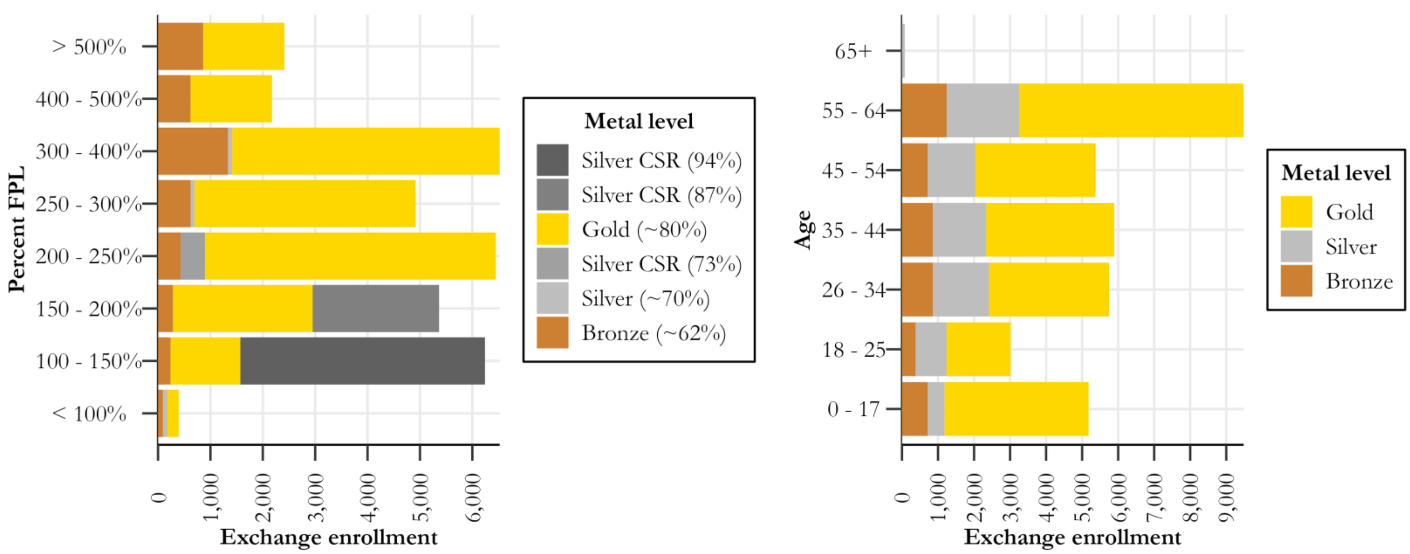
The first reason is the well-established correlation between income and health, known as the "income-health gradient."[22] On average, poorer people also tend to be sicker. So, without knowing anything else, it stands to reason that taking the poorest members of the Exchange out of the pool might improve the average health of the remaining covered lives.

This is substantiated by evidence from plan selection from the Exchange itself (Figure 14, below), which illustrates how the group likely to switch to Medicaid tends to be older and enrolled in the most generous plans:

- The panel to the left shows enrollment by income. Note that the group that will switch to Medicaid (100 - 150% FPL) are largely enrolled in the most generous plan type (94% Silver CSR). Higher actuarial value (i.e., less cost-sharing, on average) usually translates into higher utilization because there is less 'skin in the game' for the member. Higher utilization translates into higher cost.

- The panel to the right shows enrollment by age and metal level (unfortunately simplified). It's, however, clear that people who buy Silver plans (which are almost entirely the two highest CSR variants) tend to be older. Older people tend to be generally sicker and thus more expensive to insure than younger people.

Figure 14: 2022 Marketplace plan selections by income and age group[23]



[22] A good summary can be found here: https://www.irp.wisc.edu/publications/focus/pdfs/foc301b.pdf

[23] Data from CMS Marketplace Open Enrollment Public Use File (PUF) for Wyoming. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Marketplace-Products/2019_Open_Enrollment

Effects on State Finances

With the exception of the temporary ARPA incentive, the expansion of Medicaid to low-income adults **will not generate any sustainable revenue** for the State of Wyoming's government. Without any State action, any additional federal funding flowing into Wyoming would go directly to medical providers.

What expansion might do is allow for potential **State-level efficiencies** by substituting a dollar of State General Funds with 10 cents of State General Funds plus 90 cents of Federal Funds in certain programs.

Over the years, the State has created a number of programs funded largely by the State General Fund (SGF) to provide safety-net health care services to the State's most vulnerable and low-income populations. If the State expands its Medicaid program, these programs as currently conceived may no longer need to be funded at the same SGF levels, because individuals previously served by these programs will have access to comprehensive health insurance — either through Medicaid or through subsidized private plans on the Exchange.

These efficiencies are known as "offsets", and can be used to partly make up the State General Fund appropriation required to fund Medicaid Expansion. The offsets are only realized, however, if the political decision is made to **make** this substitution; i.e., by reducing State General Funds under the assumption that the providers that were paid from those Funds can make it up in Medicaid billing.

Some examples of offsets include:

- State-funded cancer screening programs;
- A handful of small Medicaid eligibility groups, currently funded at 50/50 match, could be moved to the 90/10 match under expansion;
- Health care delivered to inmates outside the prison walls (i.e., in a hospital); and,
- State-funded behavioral health services.

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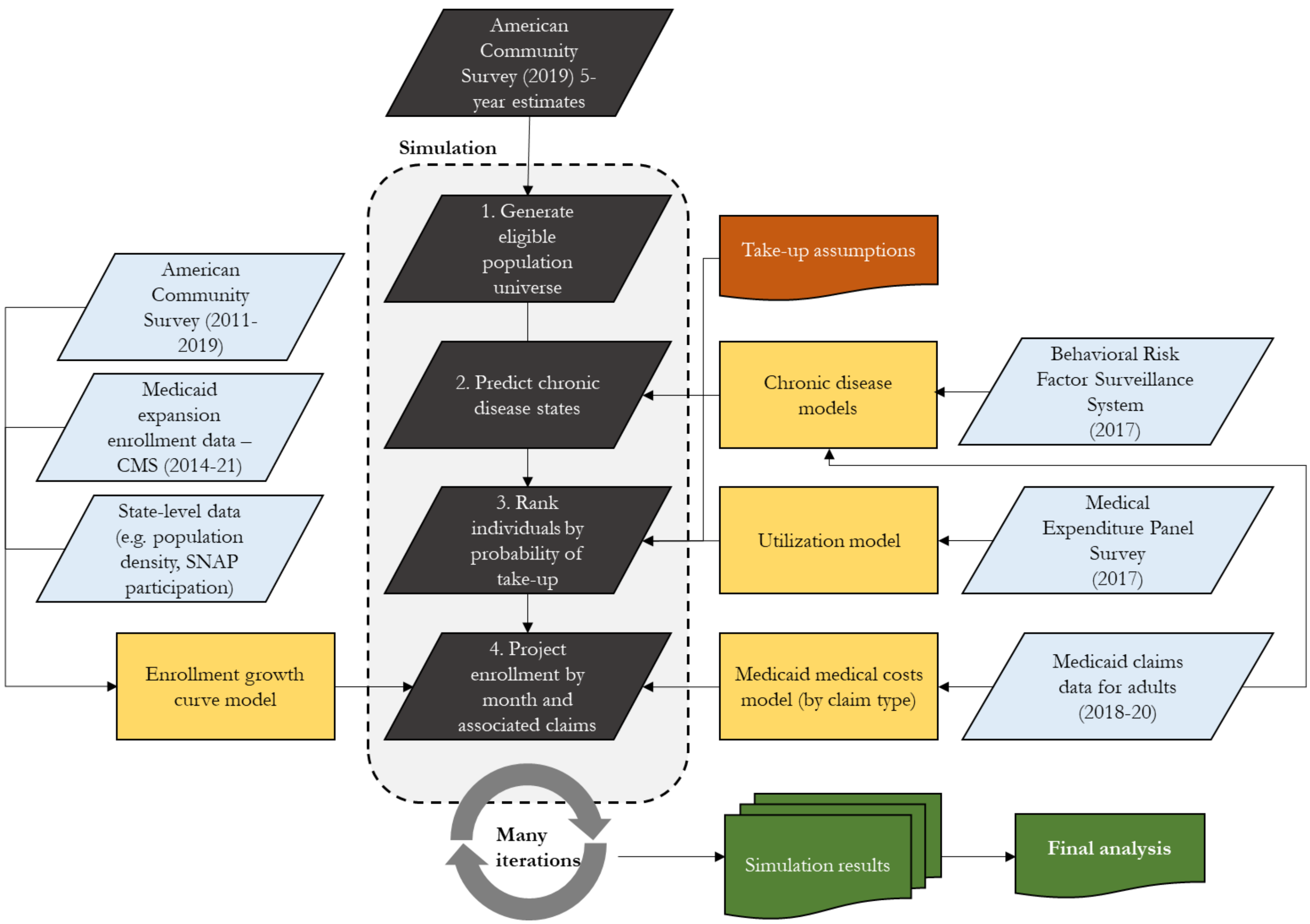
METHODOLOGY

All of the estimates in this document come from a simulation-based approach that combines the most recent and detailed Census data available for Wyoming (2019 5-year ACS estimates) with four different models to project:

- How many members will enroll in Medicaid;
- What kind of people are most likely to enroll; and,
- How much those members will incur in health care costs to the Medicaid program.

Figure 15, below, shows how the models interact with the core Census data (black) in the simulation. Narrative explaining the figure follows on the next page.

Figure 15: Medicaid expansion model framework



Generally speaking, the each iteration of the simulation follows a series of steps:

(1) We start by narrowing the universe of potentially eligible members from all Wyoming residents to civilian, non-institutionalized adults between the ages of 19 and 64 who are under 175% of the Federal Poverty Level.[24] We also exclude individuals who already have Medicare or Medicaid as their primary insurance.

- Using the person-level and replicate weights included in the Public Use Microdata Sample (PUMS), we estimate an expected total (this happens to be 51,332 in the 2019 5-year ACS data) and standard deviation (1,542) for this subset of people. For each iteration of the simulation, we then draw a value from this (assumed normal) distribution to use as the eligible population count. This allows us to propagate at least some of the measurement error of the Census microdata into the results.

- We use the replicate weight variable with the total number of people closest to this draw as the base weight for each iteration, and then use it to expand the Census microdata samples into a simulated group of people.

(2) Now we need some mechanism to **sort** the simulated group of people by their propensity to enroll in Medicaid. To do this, we make the assumption that those individuals with higher expected personal healthcare costs are more likely to enroll than those without. This is due to adverse selection (e.g., sicker people are more likely to need insurance), but also to the fact that eligibility in Medicaid can be 'retroactive,' which allows for many of the sickest members to automatically be enrolled *post hoc* if the hospital they end up in finds they are uninsured.

- The first step is to predict the **average number of chronic conditions** (out of 7 measured) in each simulated person, based on their age, sex, race/ethnicity, household income, veteran status, whether they own or rent, employment status and insurance type. The **chronic disease model** (Model 2 in the next section) is based on restricted 2017 survey data collected in Wyoming by the Behavioral Risk Factor Surveillance System (BRFSS).

- Since self-reported chronic conditions differ from those **actually diagnosed** in the Medicaid claims data, we use a second model to adjust for this and ultimately predict a unique number of chronic health conditions per simulated person.

[24] The actual income eligibility criteria for Medicaid expansion is 138% of FPL, but the simulation allows for the potential of individuals close to the eligibility criteria to intentionally reduce their income in order to qualify for health care coverage. This was done in response to surprisingly high take-up rates in some expansion states, but it does not materially affect the overall enrollment projections.

- Using the same demographic data plus the predicted number of chronic conditions, we then predict **expected (average) standardized[25] health care costs** for the simulated individuals using a model built off of 2017 Medical Expenditure Panel Survey (MEPS) data (Model 3, in the next section). While this is a national dataset (not Wyoming-specific), it covers a large universe of individuals (e.g., including the uninsured), and contains a lot of demographic information that helps model annual health care costs.

  What we're basically doing in these first three steps is generating an extensively-underwritten health insurance premium for each simulated person.

- After each member is assigned an expected total cost, we use the following **simplifying assumptions** to modify that total cost into an estimated *personal* cost (e.g., out-of-pocket costs to the individual). These include:

  - Insured individuals, whether with employer-sponsored insurance (ESI) or directly-purchased insurance, will only personally face 20% of their costs, with a maximum out-of-pocket of $5,000.[26]

  - Uninsured individuals (including those with only VA/TRICARE or IHS) will only have a willingness-to-pay that is ~20% - 35% of their total costs.[27] Health care economists generally believe this is due to the moral hazard effects of EMTALA and uncompensated/ charity care.

  - Individuals with ESI will face an approximate "hassle cost" of $1,000 in order to switch from their employer plan to Medicaid.

  - Individuals with directly-purchased insurance who are below 138% (i.e., those currently purchasing insurance on the individual ACA marketplace) will be prodded automatically to enroll in Medicaid (and subsidies for this population would be unavailable). We model this as a strong incentive of -$1,000.

  At this point, the list of individuals in the simulation is sorted by a "willingness to pay" for Medicaid coverage.

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[25] In the MEPS data, both total expenditures and utilization (visits / prescriptions / inpatient stays) are surveyed. Since prices differ across payers, we calculate average prices by aggregating expenditures and dividing by aggregate units for each utilization category (e.g., total ED costs / total ED visits). We then apply the average price for each category to the units reported by each person and add up total standardized costs to use as the outcome variable.
[26] This is based on the 20% coinsurance and approximate MOOP in the State Employees Group Insurance plan.
[27] Finkelstein, et. al. "Subsidizing health insurance for low-income adults: evidence from Massachusetts." National Bureau of Economic Research. Working Paper 23668. Page 31. Finkelstein also cites three other papers with similar estimates.

(3) Based on the **state-level enrollment model** (Model 1 in the next section), we draw a random enrollment trajectory, which estimates the total number of people enrolled in Medicaid for each month. These trajectories can be seen in the right panel of Figure 2 in the Enrollment section.

For each month of the trajectory, we fill the required number of people by drawing from the top of the "willingness to pay" list and "enrolling" them in Medicaid. This means that the people enrolling in Month 1 will also be enrolled through Month 24. We do not attempt to model churn (people losing eligibility), though this would likely be more realistic.

(4) At this point in the simulation, we have a list of Medicaid member-months, with individual demographic characteristics for all the people enrolled. Now we use the **Medicaid claims data model** (Model 4) to estimate monthly health care costs by five different claim types - Inpatient, Outpatient, Professional, Pharmacy and Dental.

Because of its structure, this model allows us to assume utilization across claim types are correlated within individuals; for example, someone with a lot of inpatient services is also likely to have a lot of professional medical claims.

These four steps show what happens inside **one single iteration** of the simulation.

Repeating the simulation for many iterations — all the while using different random draws from each model — allows us to propagate uncertainty through to the final estimates. Exploiting parallel cloud computing, we ultimately ran 1,000 iterations of the simulation this year.

Once the simulations are complete, analysis is relatively straightforward: we just ask questions of the results. How many men versus women? How many 45-50 year olds are uninsured? And so forth. The expectation (mean) of all iterations gives us the central estimate, and the remaining uncertainty in the results can be quantified by the uncertainty intervals you see throughout this document.

MODELS

All models were fit using Stan[28], with R statistical software and the brms package[29] as the interface. We used the data.table[30] and lubridate[31] packages to clean and process data, and the ggplot2[32] package to create final graphics.

Output from the brms models is shown in the next few pages. The output shows the model specification (written in lmer-like syntax), the data used, the distributional family assumed, estimates for unobserved variables, and MCMC diagnostics. Information on priors is not included in the output, but is available on request. Generally speaking, regularizing priors (e.g., Normal(0,1) for coefficients on a log or logit scale) were chosen to improve computation.

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28 Stan Development Team. 2018. RStan: the R interface to Stan. R package version 2.17.3. http://mc-stan.org
29 Paul-Christian Bürkner (2017). brms: An R Package for Bayesian Multilevel Models Using Stan. Journal of Statistical Software, 80(1), 1-28.<doi:10.18637/jss.v080.i01>
30 Matt Dowle [aut, cre], Arun Srinivasan [aut], Jan Gorecki [ctb], Michael Chirico [ctb], Pasha Stetsenko [ctb], Tom Short [ctb], Steve Lianoglou [ctb], Eduard Antonyan [ctb], Markus Bonsch [ctb], Hugh Parsonage [ctb]
31 Garrett Grolemund, Hadley Wickham (2011). Dates and Times Made Easy with lubridate. Journal of Statistical Software, 40(3), 1-25. URL http://www.jstatsoft.org/v40/i03/
32 H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2016.

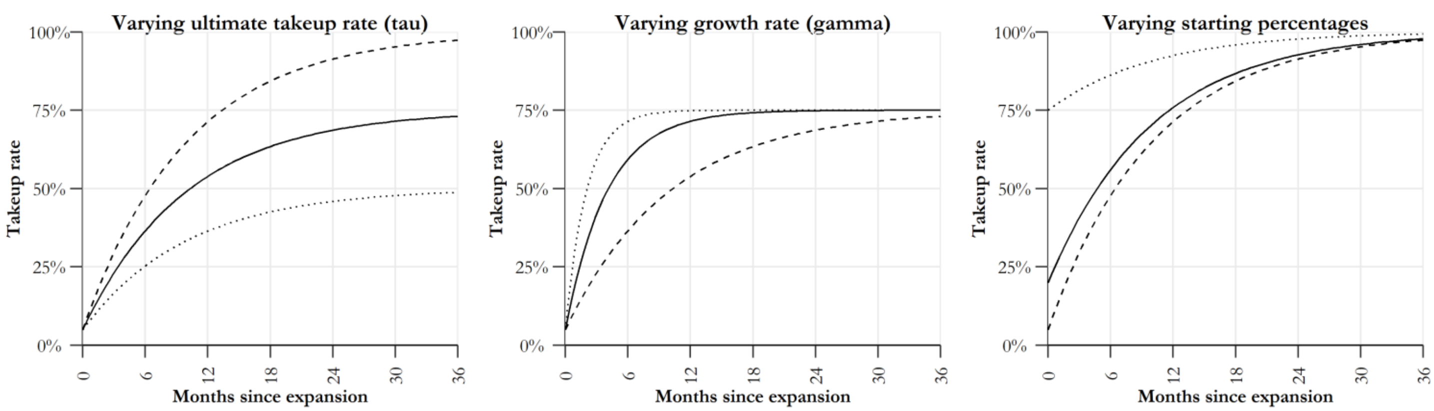
1. Enrollment model

This model attempts to estimate how Wyoming's enrollment experience may trend based on characteristics it might share with other states. The core of the enrollment model comes from monthly state Medicaid enrollment figures from CMS, covering January 2014 to December 2016.[33] These data show the enrollment trajectories for states at various stages of expansion; where some expanded Medicaid as soon as the opportunity was available (California, Colorado), others expanded later (Montana, Alaska, Louisiana).

After adding manually-gathered enrollment trajectories for states that have expanded since the CMS data expired (e.g., Maine, Idaho, Virginia, Utah, Nebraska, Oklahoma), we modeled enrollment trajectories using a parametric equation built around exponential decay, with enrollment starting at some initial level and growing more and more slowly to an asymptote defined by a percentage of the Small Area Health Insurance Estimate (SAHIE) estimate of the total eligible population. We estimated the takeup rate (tau) and growth rate (gamma) parameters as linear combinations of state-level predictors, along with correlated state-level varying intercepts.

Figure 16, below, illustrates how the three parameters of the model affect the shape of the projected enrollment curve.

Figure 16: Medicaid enrollment model parameters



Ultimately, the model with the most predictive value included the following state-level predictors:

- The Biden vote share in the 2020 election.
- The percentage of the population on food stamps (SNAP).
- State geography within the US, translated into a connected network and modeled using Markov Random Field (MRF) smooths.
- A similar MRF network created using America's Health Rankings (AHR) data and multi-dimensional scaling techniques.

[33] https://data.medicaid.gov/Enrollment/Medicaid-Enrollment-New-Adult-Group/pfrt-tr7q

```
Family: gaussian
  Links: mu = identity; sigma = log
Formula: Takeup | weights(Weight) ~ StartingPct + (exp(tau) - StartingPct) * (1 - exp(-1 *
exp(gamma) * ExpansionMonths))
         tau ~ 1 + (1 | state | STABR) + zPctBiden + zPctSNAPMedX + s(STABR2, bs = "mrf", k = 10,
xt = list(nb = geo_nb)) + s(STABR3, bs = "mrf", k = 10, xt = list(nb = ahr_nb))
         gamma ~ 1 + (1 | state | STABR) + zPctSNAPMedX
         sigma ~ 1
   Data: model_dataset_reduced (Number of observations: 452)
Samples: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup samples = 2000

Smooth Terms:
                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(tau_sSTABR2_1)     0.18      0.14     0.01     0.54 1.01      345      829
sds(tau_sSTABR3_1)     0.19      0.16     0.01     0.58 1.01      414      979

Group-Level Effects:
~STABR (Number of levels: 50)
                                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(tau_Intercept)                      0.27      0.04     0.20     0.36 1.00      516      673
sd(gamma_Intercept)                    0.42      0.07     0.29     0.58 1.01      516      952
cor(tau_Intercept,gamma_Intercept)    -0.65      0.13    -0.84    -0.37 1.01      527      982

Population-Level Effects:
                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma_Intercept       -3.72      0.04    -3.79    -3.64 1.00     1938     1373
tau_Intercept         -0.35      0.05    -0.45    -0.25 1.01      381      730
tau_zPctBiden          0.09      0.05    -0.00     0.19 1.01      528      535
tau_zPctSNAPMedX       0.04      0.05    -0.05     0.16 1.01      643      890
gamma_Intercept       -2.50      0.08    -2.66    -2.35 1.01      640     1063
gamma_zPctSNAPMedX     0.19      0.09     0.01     0.36 1.02      557      921

Samples were drawn 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). 7
```

2. Chronic disease count models

The first model draws upon Wyoming Behavioral Risk Factor Surveillance System (BRFSS) microdata to estimate the total count of 7 potential chronic diseases in individuals based demographic factors that are also available in the American Community Survey Census data (race/ethnicity, veteran status, employment, household income, insurance status, age and sex). We also include varying effects for survey meta-data (interviewer, county, month).

The specific diseases included in this count include:

- Heart disease;
- Heart attack in last twelve months;
- Hypertension;
- Diabetes;
- Chronic Obstructive Pulmonary Disease (COPD);
- Depression / mood disorder;
- Joint disease;
- Asthma;

Since this is a count model, we use a truncated Poisson likelihood with log-link on the linear predictors.

```
Family: poisson
  Links: mu = log
Formula: nChronic | trunc(ub = 7) ~ 1 + t2(AGE, EMPINS, bs = c("cr", "re"), k = c(5, 6)) +
RACE + OWNRENT + +INCOME + (1 | IMONTH) + (1 | INTVID) + (1 | COUNTY)
   Data: wy_2017_subset (Number of observations: 4463)
Samples: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup samples = 2000

Smooth Terms:
                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(t2AGEEMPINS_1)     1.07      0.27     0.64     1.69 1.00      656      949
sds(t2AGEEMPINS_2)     1.35      0.31     0.85     2.05 1.00      835      956

Group-Level Effects:
~COUNTY (Number of levels: 23)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.08      0.02     0.03     0.13 1.00      688      910

~IMONTH (Number of levels: 12)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.02      0.01     0.00     0.05 1.00     1051      638

~INTVID (Number of levels: 424)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.05      0.03     0.00     0.11 1.00      336      546



Population-Level Effects:
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
```

```
Intercept          0.47       0.19     0.10      0.87 1.00      712      723
RACEAsian         -0.20       0.33    -0.87      0.42 1.00     2155     1210
RACEBlack         -0.19       0.20    -0.58      0.22 1.00     1327     1513
RACEHispanic       0.02       0.13    -0.23      0.28 1.00      912     1169
RACEOther          0.00       0.15    -0.28      0.31 1.00     1043     1426
RACEWhite         -0.04       0.12    -0.26      0.19 1.00      861     1177
OWNRENT           -0.26       0.04    -0.34     -0.19 1.01     2290     1597
INCOME25K         -0.11       0.06    -0.22      0.00 1.00     1157     1263
INCOME35K         -0.20       0.06    -0.32     -0.08 1.00     1100     1285
INCOME50K         -0.24       0.06    -0.35     -0.12 1.00     1073     1431
INCOME50Kplus     -0.40       0.05    -0.51     -0.30 1.00      951     1234
INCOMEOther       -0.39       0.06    -0.50     -0.27 1.00     1075     1251

Samples were drawn 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).
```

The second chronic disease model is similar, but intended to translate the self-reported BRFSS conditions into the diagnosed conditions counted in the Medicaid claims data.

To do this, we first applied the expected chronic conditions from the first model on the claims data — assuming that all Family Care adult incomes were in the lowest category and that members were not in the labor force. We then fit the second model (outcome being conditions diagnosed in the Medicaid claims data) based on age, sex, race and this new estimated "chronic condition risk" score.

In order to better fit the under-dispersed data, we used a Conway-Maxwell-Poisson distributional assumption, as well as the truncation to limit predicted conditions to the seven (7) measured.

```
Family: com_poisson
  Links: mu = log; shape = identity
Formula: dxChronic | trunc(ub = 7) ~ 1 + t2(Estimate, AGE, RACE, GENDER, bs = c("cr", "cr",
"re", "re"), k = c(3, 3, 6, 3))
   Data: model_dataset_fitted (Number of observations: 2079)
Samples: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup samples = 2000

Smooth Terms:
                               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(t2EstimateAGERACEGENDER_1)     0.60      0.49     0.02     1.82 1.00     1409     1267
sds(t2EstimateAGERACEGENDER_2)     0.66      0.54     0.02     2.04 1.00     1123     1110
sds(t2EstimateAGERACEGENDER_3)     0.59      0.49     0.02     1.78 1.00     1437     1306
sds(t2EstimateAGERACEGENDER_4)     3.57      0.75     2.33     5.29 1.00     1056     1174

Population-Level Effects:
          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept    -0.54      0.20    -0.99    -0.17 1.00     1107      758

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     0.47      0.05     0.38     0.57 1.00     1749      839

Samples were drawn 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).
```

Utilization models

Both the MEPS and Medicaid models are built to model two unique features of aggregate health care costs:

- A significant number of zero-cost person-periods, for people that do not use any health care in the time period.

- For those who do use care, the costs have a skewed distribution with a long right tail, due to the few individuals who may have extremely high costs in that period.

Structurally, therefore, they are built around similar distributional assumptions, so we use the same "hurdle lognormal" framework, where probability of **any** costs is modeled first (the "hurdle"), and if there are costs in the time period, those costs are modeled using a lognormal distribution.

There are, however, several important differences between the two models:

- The MEPS model uses more demographic predictors (e.g., insurance status, educational attainment, race) that aren't available in the Medicaid data. Both use age and the count of chronic conditions estimated in Model 2.

- Where the MEPS model is straightforward (e.g., annual costs per person), the Medicaid model is hierarchical, in the sense that data for member-months are nested both within members (e.g., "Bob") and months ("January").

  The Medicaid model therefore takes advantage of this hierarchical nature to estimates varying intercepts for both individual members, effectively allowing us to simulate "sicker" and "healthier" people in the data.

- Where the MEPS model looks at total cost, the Medicaid claims model considers five different components of cost simultaneously (inpatient, outpatient, professional, dental, and pharmacy). The model also leverages the individual varying-intercepts structure to estimate correlations within individuals between the five claim types for the hurdle component (probability of using care).

- The MEPS model is fit on nationally-representative survey data. The Medicaid claims model is fit on Wyoming Medicaid claims data for low-income (Family Care) adults and "children" between the ages of 19 and 64.

3. MEPS utilization model

```
Family: hurdle_lognormal
  Links: mu = identity; sigma = identity; hu = logit
Formula: UScore ~ 1 + Male + s(zAge, zChronic, zPOV) + (1 | VARSTR)
         hu ~ 1 + Male * zAge + zChronic + zPOV + (1 | VARSTR)
   Data: model_sample (Number of observations: 4875)
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup samples = 4000

Smooth Terms:
                         Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(szAgezChroniczPOV_1)     2.44      0.40     1.73     3.30 1.00     3041     3074

Group-Level Effects:
~VARSTR (Number of levels: 165)
                 Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)        0.16      0.03     0.09     0.22 1.00     1639     1799
sd(hu_Intercept)     0.24      0.07     0.09     0.35 1.00      898      789

Population-Level Effects:
                    Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept               7.50      0.03     7.44     7.56 1.00     6866     3351
hu_Intercept           -5.50      0.24    -5.98    -5.03 1.00     7588     3074
Male                   -0.25      0.04    -0.32    -0.17 1.00    10009     2732
hu_Male                 0.74      0.07     0.60     0.88 1.00    10703     2843
hu_zAge                 0.15      0.09    -0.02     0.32 1.00     6073     3280
hu_zChronic            -3.15      0.17    -3.48    -2.82 1.00     7476     3073
hu_zPOV                -0.28      0.04    -0.35    -0.20 1.00    11054     2649
hu_Male:zAge           -0.58      0.12    -0.81    -0.34 1.00     5624     2942
szAgezChroniczPOV_1    -0.01      0.96    -1.89     1.89 1.00     9405     3220
szAgezChroniczPOV_2    -0.91      0.59    -2.11     0.26 1.00     6112     2844
szAgezChroniczPOV_3     0.01      0.97    -1.87     1.93 1.00    10290     2930
szAgezChroniczPOV_4     0.84      0.95    -1.05     2.66 1.00     9356     3079
szAgezChroniczPOV_5    -1.25      0.97    -3.09     0.63 1.00     8481     3305
szAgezChroniczPOV_6    -0.87      0.60    -2.04     0.31 1.00     7420     3268
szAgezChroniczPOV_7     0.36      0.82    -1.24     1.96 1.00    10410     3178
szAgezChroniczPOV_8    -0.44      0.67    -1.80     0.88 1.00     9052     3091
szAgezChroniczPOV_9     0.88      0.69    -0.50     2.23 1.00     7456     3230

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma     1.14      0.01     1.11     1.16 1.00     8104     2657
```

4. Medicaid claims data model

```
Family: MV(hurdle_lognormal, hurdle_lognormal, hurdle_lognormal, hurdle_lognormal,
hurdle_lognormal)
  Links: mu = identity; sigma = identity; hu = logit
         mu = identity; sigma = identity; hu = logit
         mu = identity; sigma = identity; hu = logit
         mu = identity; sigma = identity; hu = logit
         mu = identity; sigma = identity; hu = logit
Formula: D ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE +
s(MonthNo, k = 3, bs = "cr") + (1 | id | ID)
         hu ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE + (1 |
id | ID)
         I ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE +
s(MonthNo, k = 3, bs = "cr") + (1 | id | ID)
         hu ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE + (1 |
id | ID)
```

```
        M ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE +
s(MonthNo, k = 3, bs = "cr") + (1 | id | ID)
        hu ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE + (1 |
id | ID)
        O ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE +
s(MonthNo, k = 3, bs = "cr") + (1 | id | ID)
        hu ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE + (1 |
id | ID)
        P ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE +
s(MonthNo, k = 3, bs = "cr") + (1 | id | ID)
        hu ~ 1 + s(Age, k = 3, bs = "cr") + s(nChronic, k = 3, bs = "cr") + GENDER + RACE + (1 |
id | ID)
   Data: model_dataset (Number of observations: 24948)
Samples: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
        total post-warmup samples = 2000

Smooth Terms:
                      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(D_sAge_1)             0.67      0.44     0.14     1.78 1.00     1578     1481
sds(D_snChronic_1)        0.41      0.43     0.01     1.63 1.00     1256     1318
sds(D_sMonthNo_1)         0.41      0.42     0.01     1.52 1.00      933      964
sds(hu_D_sAge_1)          0.43      0.45     0.01     1.69 1.00     1093     1331
sds(hu_D_snChronic_1)     0.72      0.51     0.05     1.87 1.00     1176      766
sds(I_sAge_1)             0.45      0.44     0.01     1.68 1.00      971     1264
sds(I_snChronic_1)        0.49      0.46     0.01     1.70 1.00     1014      979
sds(I_sMonthNo_1)         0.45      0.44     0.01     1.68 1.00     1002     1116
sds(hu_I_sAge_1)          0.55      0.48     0.02     1.77 1.00     1225     1251
sds(hu_I_snChronic_1)     0.97      0.51     0.24     2.21 1.00     2068     1493
sds(M_sAge_1)             0.39      0.43     0.01     1.54 1.01      797     1065
sds(M_snChronic_1)        0.42      0.44     0.01     1.64 1.00     1180     1259
sds(M_sMonthNo_1)         0.52      0.43     0.07     1.64 1.00     1021     1120
sds(hu_M_sAge_1)          0.49      0.45     0.02     1.71 1.00      836      845
sds(hu_M_snChronic_1)     1.30      0.52     0.56     2.55 1.00     2677     1196
sds(O_sAge_1)             0.53      0.45     0.05     1.67 1.00     1166     1136
sds(O_snChronic_1)        0.47      0.44     0.02     1.65 1.00     1425     1441
sds(O_sMonthNo_1)         0.42      0.44     0.01     1.62 1.00      902      929
sds(hu_O_sAge_1)          0.43      0.42     0.01     1.59 1.00      501      820
sds(hu_O_snChronic_1)     1.02      0.48     0.37     2.18 1.00     2347     1235
sds(P_sAge_1)             0.42      0.44     0.01     1.67 1.00     1325     1491
sds(P_snChronic_1)        0.44      0.44     0.01     1.62 1.00     1493     1617
sds(P_sMonthNo_1)         0.32      0.40     0.00     1.46 1.01      763     1027
sds(hu_P_sAge_1)          0.61      0.47     0.05     1.79 1.00     1282     1072
sds(hu_P_snChronic_1)     1.48      0.50     0.74     2.69 1.00     1871     1025

Group-Level Effects:
~ID (Number of levels: 2079)
                                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(D_Intercept)                        0.19      0.06     0.06     0.31 1.06       62      205
sd(hu_D_Intercept)                     1.12      0.07     0.99     1.25 1.01      632     1225
sd(I_Intercept)                        0.31      0.11     0.07     0.52 1.01      217      687
sd(hu_I_Intercept)                     1.44      0.12     1.21     1.69 1.00     1108     1372
sd(M_Intercept)                        0.74      0.02     0.70     0.78 1.00     1276     1546
sd(hu_M_Intercept)                     1.51      0.04     1.44     1.59 1.00     1301     1394
sd(O_Intercept)                        0.69      0.03     0.64     0.75 1.00     1210     1314
sd(hu_O_Intercept)                     1.30      0.04     1.23     1.38 1.00     1822     1618
sd(P_Intercept)                        1.15      0.02     1.11     1.20 1.00     1215     1560
sd(hu_P_Intercept)                     2.10      0.05     1.99     2.21 1.00     1216     1572
cor(D_Intercept,hu_D_Intercept)        0.16      0.20    -0.28     0.54 1.16       21       62
cor(D_Intercept,I_Intercept)          -0.18      0.28    -0.68     0.40 1.06       56      528
cor(hu_D_Intercept,I_Intercept)        0.11      0.24    -0.39     0.56 1.01     1455     1372
cor(D_Intercept,hu_I_Intercept)        0.19      0.20    -0.23     0.56 1.15       23      103
cor(hu_D_Intercept,hu_I_Intercept)    -0.01      0.11    -0.21     0.20 1.01      471     1057
cor(I_Intercept,hu_I_Intercept)       -0.35      0.19    -0.72     0.05 1.19       15       58
```

```
cor(D_Intercept,M_Intercept)         -0.28      0.21     -0.65     0.15 1.36       10        28
cor(hu_D_Intercept,M_Intercept)      -0.04      0.05     -0.14     0.07 1.01      538       904
cor(I_Intercept,M_Intercept)          0.48      0.18      0.07     0.76 1.18       15       127
cor(hu_I_Intercept,M_Intercept)      -0.62      0.07     -0.74    -0.47 1.02      226       897
cor(D_Intercept,hu_M_Intercept)      -0.06      0.18     -0.52     0.24 1.37       10        18
cor(hu_D_Intercept,hu_M_Intercept)    0.34      0.04      0.26     0.43 1.01      358       648
cor(I_Intercept,hu_M_Intercept)      -0.14      0.21     -0.56     0.29 1.31       11        51
cor(hu_I_Intercept,hu_M_Intercept)    0.48      0.07      0.33     0.62 1.03       97       234
cor(M_Intercept,hu_M_Intercept)      -0.15      0.04     -0.23    -0.08 1.01      720      1227
cor(D_Intercept,O_Intercept)          0.15      0.16     -0.17     0.48 1.09       37        58
cor(hu_D_Intercept,O_Intercept)      -0.15      0.06     -0.27    -0.02 1.02      400       645
cor(I_Intercept,O_Intercept)          0.11      0.21     -0.32     0.49 1.24       13        41
cor(hu_I_Intercept,O_Intercept)      -0.56      0.07     -0.69    -0.41 1.04      112       479
cor(M_Intercept,O_Intercept)          0.29      0.04      0.20     0.37 1.00     1352      1785
cor(hu_M_Intercept,O_Intercept)      -0.32      0.04     -0.40    -0.23 1.00     1447      1345
cor(D_Intercept,hu_O_Intercept)       0.01      0.15     -0.31     0.30 1.17       20        61
cor(hu_D_Intercept,hu_O_Intercept)    0.28      0.05      0.18     0.37 1.01      435       881
cor(I_Intercept,hu_O_Intercept)      -0.21      0.20     -0.56     0.23 1.23       13        18
cor(hu_I_Intercept,hu_O_Intercept)    0.64      0.06      0.52     0.76 1.06       45       266
cor(M_Intercept,hu_O_Intercept)      -0.30      0.04     -0.38    -0.23 1.01      951      1212
cor(hu_M_Intercept,hu_O_Intercept)    0.70      0.02      0.66     0.74 1.01      890      1633
cor(O_Intercept,hu_O_Intercept)      -0.65      0.04     -0.72    -0.57 1.00      641      1192
cor(D_Intercept,P_Intercept)          0.24      0.13     -0.01     0.49 1.28       11        48
cor(hu_D_Intercept,P_Intercept)      -0.04      0.05     -0.14     0.06 1.01      362       673
cor(I_Intercept,P_Intercept)          0.07      0.14     -0.18     0.38 1.06       43        96
cor(hu_I_Intercept,P_Intercept)      -0.32      0.06     -0.43    -0.21 1.04      140       482
cor(M_Intercept,P_Intercept)          0.24      0.03      0.18     0.31 1.00      928      1450
cor(hu_M_Intercept,P_Intercept)      -0.25      0.03     -0.31    -0.18 1.00      888      1352
cor(O_Intercept,P_Intercept)          0.30      0.04      0.22     0.37 1.00      936      1299
cor(hu_O_Intercept,P_Intercept)      -0.36      0.03     -0.42    -0.30 1.00      880      1388
cor(D_Intercept,hu_P_Intercept)      -0.19      0.14     -0.48     0.07 1.17       20        50
cor(hu_D_Intercept,hu_P_Intercept)    0.29      0.04      0.20     0.38 1.00      506      1047
cor(I_Intercept,hu_P_Intercept)       0.01      0.24     -0.46     0.43 1.36       10        48
cor(hu_I_Intercept,hu_P_Intercept)    0.21      0.08      0.06     0.35 1.05       66       281
cor(M_Intercept,hu_P_Intercept)      -0.25      0.04     -0.32    -0.18 1.00      883      1496
cor(hu_M_Intercept,hu_P_Intercept)    0.66      0.02      0.62     0.69 1.00     1199      1541
cor(O_Intercept,hu_P_Intercept)      -0.23      0.05     -0.32    -0.13 1.01      853      1500
cor(hu_O_Intercept,hu_P_Intercept)    0.64      0.02      0.60     0.68 1.00     1164      1821
cor(P_Intercept,hu_P_Intercept)      -0.49      0.03     -0.55    -0.44 1.01      835      1447
```

```
Population-Level Effects:
                  Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
D_Intercept           5.44      0.11     5.23     5.65 1.04      112      799
hu_D_Intercept        4.08      0.17     3.77     4.43 1.00     1635     1596
I_Intercept           8.65      0.17     8.31     8.97 1.02      330     1166
hu_I_Intercept        5.25      0.28     4.73     5.81 1.01     1483     1439
M_Intercept           4.89      0.08     4.73     5.03 1.00     1229     1504
hu_M_Intercept        1.09      0.12     0.87     1.34 1.00      979     1299
O_Intercept           6.26      0.07     6.13     6.39 1.00     1551     1669
hu_O_Intercept        0.65      0.10     0.45     0.86 1.00     1074     1459
P_Intercept           5.75      0.09     5.58     5.93 1.00     1382     1297
hu_P_Intercept        0.24      0.15    -0.05     0.54 1.00     1155     1411
D_GENDERM             0.05      0.06    -0.07     0.17 1.00     2994     1800
D_RACEAsian          -0.70      0.30    -1.30    -0.08 1.00     3685     1415
D_RACEBlack          -0.15      0.22    -0.59     0.28 1.00     2842     1671
D_RACEHispanic       -0.48      0.14    -0.78    -0.21 1.01     1288     1565
D_RACEOther          -0.40      0.13    -0.65    -0.15 1.00     1917     1675
D_RACEWhite          -0.47      0.10    -0.68    -0.27 1.01     1321     1376
hu_D_GENDERM          0.27      0.10     0.08     0.46 1.00     2304     1889
hu_D_RACEAsian       -0.85      0.51    -1.81     0.19 1.00     1823     1246
hu_D_RACEBlack       -0.54      0.37    -1.24     0.21 1.00     1785     1330
hu_D_RACEHispanic    -0.35      0.23    -0.80     0.07 1.00     1898     1730
hu_D_RACEOther       -0.19      0.20    -0.58     0.20 1.00     1733     1620
```

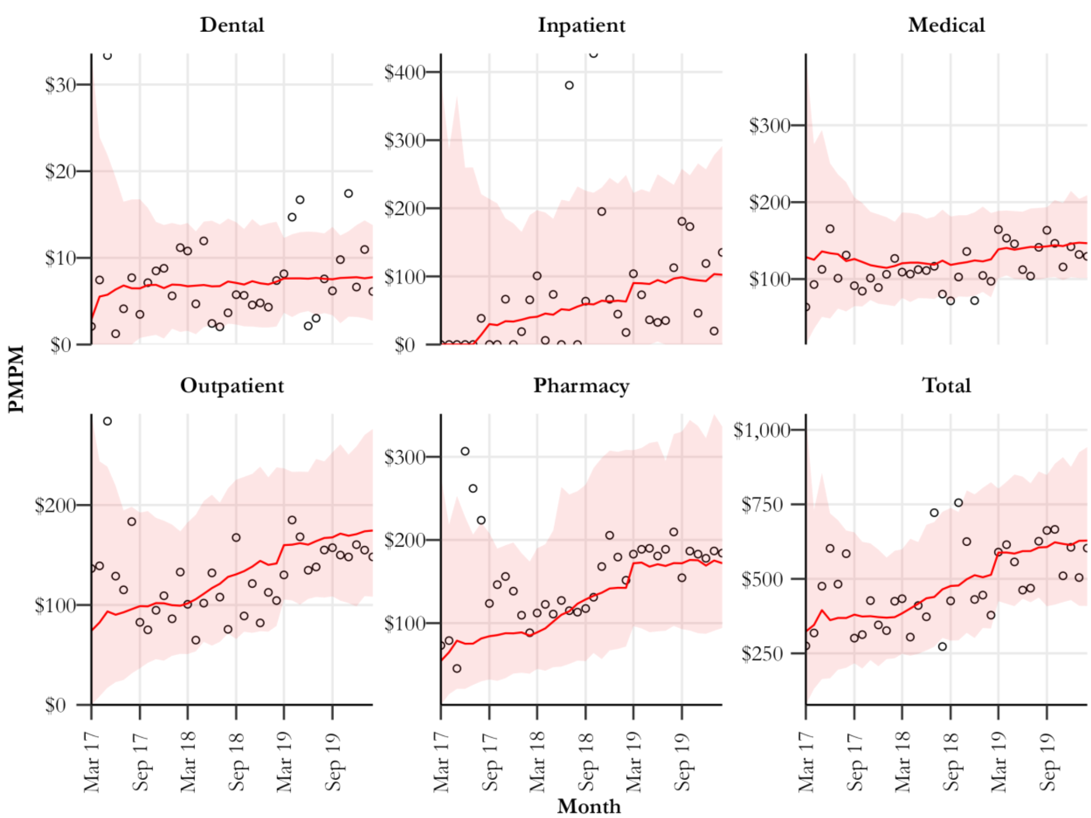
hu_D_RACEWhite	-0.31	0.16	-0.63	0.01	1.00	1652	1446
I_GENDERM	0.00	0.13	-0.24	0.24	1.00	2210	1838
I_RACEAsian	-1384.88	320.60	-2010.32	-773.23	1.00	3348	1301
I_RACEBlack	-0.27	0.39	-1.03	0.49	1.00	2699	1562
I_RACEHispanic	-0.14	0.29	-0.68	0.42	1.01	1556	1617
I_RACEOther	0.11	0.27	-0.41	0.63	1.00	2722	1518
I_RACEWhite	0.06	0.16	-0.24	0.36	1.00	2209	1817
hu_I_GENDERM	0.32	0.20	-0.06	0.70	1.00	3172	1810
hu_I_RACEAsian	89.19	86.58	4.06	315.58	1.00	1098	843
hu_I_RACEBlack	0.94	0.67	-0.32	2.38	1.00	1722	1709
hu_I_RACEHispanic	1.28	0.45	0.41	2.19	1.00	2443	1914
hu_I_RACEOther	1.56	0.40	0.80	2.39	1.00	2322	1691
hu_I_RACEWhite	1.17	0.25	0.68	1.65	1.00	1788	1690
M_GENDERM	0.02	0.05	-0.08	0.11	1.00	1746	1477
M_RACEAsian	-0.63	0.28	-1.16	-0.07	1.00	1775	1703
M_RACEBlack	-0.28	0.19	-0.67	0.08	1.00	1648	1580
M_RACEHispanic	-0.44	0.11	-0.65	-0.22	1.00	1240	1040
M_RACEOther	-0.34	0.10	-0.53	-0.15	1.00	1467	1660
M_RACEWhite	-0.22	0.08	-0.38	-0.06	1.00	1408	1788
hu_M_GENDERM	0.68	0.08	0.54	0.84	1.01	1664	1326
hu_M_RACEAsian	-0.27	0.48	-1.21	0.66	1.00	1019	1223
hu_M_RACEBlack	-0.42	0.33	-1.06	0.22	1.00	1303	1524
hu_M_RACEHispanic	-0.69	0.19	-1.05	-0.33	1.00	1162	1346
hu_M_RACEOther	-0.47	0.16	-0.78	-0.14	1.00	1166	1415
hu_M_RACEWhite	-0.65	0.12	-0.90	-0.41	1.00	1094	1369
O_GENDERM	-0.09	0.05	-0.19	0.00	1.00	1914	1415
O_RACEAsian	-0.90	0.32	-1.51	-0.27	1.00	2185	1456
O_RACEBlack	-1.54	0.20	-1.95	-1.16	1.00	1794	1605
O_RACEHispanic	-1.14	0.11	-1.37	-0.91	1.00	1560	1539
O_RACEOther	-1.12	0.10	-1.32	-0.92	1.00	1883	1780
O_RACEWhite	-1.21	0.07	-1.35	-1.07	1.00	1490	1687
hu_O_GENDERM	0.53	0.07	0.39	0.68	1.00	1428	1636
hu_O_RACEAsian	1.24	0.47	0.32	2.12	1.00	1153	900
hu_O_RACEBlack	1.15	0.29	0.59	1.74	1.00	1248	1605
hu_O_RACEHispanic	1.25	0.17	0.91	1.58	1.00	1183	1390
hu_O_RACEOther	1.47	0.14	1.19	1.76	1.00	1402	1472
hu_O_RACEWhite	1.24	0.10	1.03	1.45	1.00	1028	1322
P_GENDERM	-0.14	0.06	-0.26	-0.02	1.00	1708	1679
P_RACEAsian	-2.38	0.39	-3.16	-1.63	1.00	2016	1456
P_RACEBlack	-2.29	0.27	-2.83	-1.74	1.00	2248	1375
P_RACEHispanic	-2.10	0.15	-2.38	-1.82	1.00	1494	1531
P_RACEOther	-2.27	0.12	-2.52	-2.02	1.00	1768	1604
P_RACEWhite	-2.21	0.09	-2.40	-2.04	1.00	1287	1366
hu_P_GENDERM	0.89	0.11	0.69	1.10	1.00	1382	1402
hu_P_RACEAsian	1.32	0.68	-0.06	2.63	1.00	1340	1136
hu_P_RACEBlack	0.80	0.44	-0.08	1.64	1.00	1672	1559
hu_P_RACEHispanic	0.40	0.25	-0.09	0.88	1.00	1192	1084
hu_P_RACEOther	0.52	0.22	0.09	0.94	1.00	1226	1001
hu_P_RACEWhite	0.31	0.16	0.00	0.62	1.00	1147	1215
D_sAge_1	-0.12	0.11	-0.33	0.10	1.00	2606	1383
D_snChronic_1	0.00	0.11	-0.21	0.22	1.00	2121	1775
D_sMonthNo_1	-0.06	0.08	-0.23	0.10	1.00	3528	1630
hu_D_sAge_1	0.53	0.16	0.23	0.84	1.00	2052	1599
hu_D_snChronic_1	-0.25	0.22	-0.67	0.21	1.00	1269	1448
I_sAge_1	0.50	0.19	0.14	0.89	1.02	161	1479
I_snChronic_1	0.17	0.15	-0.12	0.46	1.00	1893	1448
I_sMonthNo_1	0.14	0.18	-0.24	0.48	1.02	148	822
hu_I_sAge_1	-0.08	0.27	-0.62	0.46	1.00	2430	1670
hu_I_snChronic_1	-1.52	0.28	-2.07	-0.98	1.00	1351	1425
M_sAge_1	0.06	0.07	-0.08	0.20	1.00	1782	1654
M_snChronic_1	0.78	0.09	0.60	0.95	1.00	1303	1549
M_sMonthNo_1	-0.24	0.06	-0.35	-0.12	1.00	2020	1424
hu_M_sAge_1	0.41	0.13	0.14	0.66	1.00	1357	1418

```
hu_M_snChronic_1     -1.32      0.21     -1.73     -0.90 1.00      1405      1649
O_sAge_1             -0.07      0.08     -0.22      0.08 1.00      1642      1624
O_snChronic_1         0.24      0.09      0.05      0.42 1.00      1255      1597
O_sMonthNo_1         -0.00      0.07     -0.13      0.13 1.00      2125      1680
hu_O_sAge_1           0.32      0.12      0.09      0.55 1.00      1310      1439
hu_O_snChronic_1     -1.16      0.17     -1.47     -0.84 1.00       999      1360
P_sAge_1              0.32      0.10      0.12      0.52 1.00      1678      1542
P_snChronic_1         1.00      0.12      0.75      1.23 1.00      1261      1201
P_sMonthNo_1          0.05      0.06     -0.06      0.17 1.00      2652      1287
hu_P_sAge_1          -0.70      0.18     -1.06     -0.36 1.00      1476      1543
hu_P_snChronic_1     -1.32      0.28     -1.88     -0.76 1.00      1270      1308

Family Specific Parameters:
        Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma_D     0.79      0.02     0.75     0.84 1.02      245     1113
sigma_I     0.73      0.05     0.62     0.83 1.01      293      916
sigma_M     1.15      0.01     1.13     1.16 1.00     2669     1622
sigma_O     1.08      0.01     1.05     1.10 1.00     2521     1625
sigma_P     0.95      0.01     0.93     0.96 1.00     2794     1407

Samples were drawn 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).
```

Careful readers will note some low effective sample sizes and convergence issues (Rhats ~ 1.3) on some of the group-level correlation parameters. From posterior predictive checks on the Family Care adult claims data, we do not believe these create any issues when predicting health care claims on the population level. The figure below shows an example, predicting PMPM costs for ~ 1,000 randomly-selected and de-identified Family Care individuals based on modeled characteristics alone.



5. Direct insurance utilization model

This model is only used to estimate the standardized health care costs of individuals who might be crowded-out of the direct insurance market. The data is similar to the MEPS model, but restricted to individuals with directly-purchased insurance.

```
Family: hurdle_lognormal Links: mu = identity; sigma = identity; hu = logit
Formula: UScore ~ 1 + s(Chronic, k = 3) + s(zAge, k = 3) + Male + Race + Education + zPOV +
(1 | VARSTR)
         hu ~ 1 + Chronic + zAge + Male + Race + Education + zPOV + (1 | VARSTR)
   Data: model_dataset (Number of observations: 3942)
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
         total post-warmup samples = 4000

Smooth Terms:
                Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(sChronic_1)     0.77      0.59     0.03     2.19 1.00     3596     1865
sds(szAge_1)        0.58      0.49     0.02     1.85 1.00     2758     2301

Group-Level Effects:
~VARSTR (Number of levels: 165)
                 Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)        0.13      0.05     0.02     0.22 1.00      709      932
sd(hu_Intercept)     0.23      0.07     0.06     0.35 1.00      871      591

Population-Level Effects:
                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                7.05      0.28     6.50     7.59 1.00     1520     2221
hu_Intercept            -0.32      0.34    -1.01     0.34 1.00     1497     1891
Male                    -0.30      0.04    -0.39    -0.22 1.00     9360     2789
RaceAsian               -0.23      0.28    -0.76     0.32 1.01     1514     2275
RaceBlack               -0.24      0.27    -0.76     0.29 1.00     1474     2211
RaceHispanic            -0.30      0.27    -0.83     0.24 1.01     1483     2256
RaceOther                0.08      0.29    -0.48     0.65 1.00     1478     2194
RaceWhite                0.10      0.27    -0.41     0.64 1.00     1482     2055
EducationGraduate        0.05      0.13    -0.20     0.31 1.00     5659     3358
EducationHSDGED          0.01      0.07    -0.13     0.15 1.00     3229     3221
EducationNodegree       -0.13      0.10    -0.32     0.06 1.00     4123     3376
EducationOther           0.02      0.10    -0.19     0.22 1.00     4185     3128
EducationUnknown         0.04      0.08    -0.12     0.19 1.00     3151     3251
zPOV                    -0.07      0.03    -0.12    -0.02 1.00     7883     2623
hu_Chronic              -0.80      0.07    -0.93    -0.67 1.00     6464     3107
hu_zAge                  0.09      0.05    -0.01     0.18 1.00     5901     2926
hu_Male                  0.65      0.07     0.51     0.79 1.00     6943     3144
hu_RaceAsian            -0.24      0.34    -0.91     0.43 1.00     1463     2071
hu_RaceBlack            -0.14      0.33    -0.77     0.52 1.00     1460     2128
hu_RaceHispanic         -0.22      0.32    -0.86     0.43 1.00     1442     2089
hu_RaceOther            -0.87      0.36    -1.57    -0.15 1.00     1686     2301
hu_RaceWhite            -0.93      0.33    -1.56    -0.28 1.00     1450     1876
hu_EducationGraduate    -0.53      0.24    -1.00    -0.07 1.00     5499     2784
hu_EducationHSDGED       0.31      0.12     0.07     0.56 1.00     2658     3197
hu_EducationNodegree     0.28      0.16    -0.02     0.58 1.00     3473     3412
hu_EducationOther        0.09      0.18    -0.27     0.44 1.00     3445     3257
hu_EducationUnknown      0.11      0.13    -0.14     0.36 1.00     2976     3267
hu_zPOV                 -0.00      0.05    -0.09     0.08 1.00     9087     2908
sChronic_1              -0.36      0.03    -0.41    -0.29 1.00     4413     2831
szAge_1                 -0.14      0.03    -0.20    -0.08 1.00     7076     3182

Family Specific Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma     1.09      0.02     1.06     1.13 1.00     5269     2557
```