Medicaid Expansion In Wyoming

Enrollment and Cost Projections

Wyoming Department of Health
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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 $18 million State Funds and $135 million Federal Funds.** There are three important caveats:

- The estimate comes with uncertainty — for State Funds, we're 90% sure it will be $11 - $26 million;
- It assumes an enrollment growth curve that begins at zero and continues to grow well past two years, so subsequent biennial appropriations will necessarily be larger; and,
- It assumes a "vanilla" expansion of Medicaid, without the kind of bells and whistles that would require a waiver.

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

- We anticipate approximately 19,000 new Medicaid enrollees by the end of the first biennium. While this figure is similar to the original (2011) Milliman estimate, we project:
    - A wider range of uncertainty, with 90% of scenarios falling between 9,000 and 32,000 people at the 24-month mark.
    - That the 24-month estimate is only part of a larger enrollment trajectory that will continue to grow before flattening out after 36 months.
- Of those enrolling:
    - Approximately two-thirds of individuals will have incomes in the insurance coverage gap (100% FPL or less);
    - ~ 56% will have previously been uninsured (the remainder having some form of insurance coverage today); and,
    - ~50% 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 (i.e., previously insured members moving to Medicaid). These include:
    - Significant (~50-67%) attenuation of new revenue to providers due to Medicaid rates being lower than commercial rates, though net provider revenue will almost certainly remain positive.
    - A probable (though not guaranteed) 5 to 15% decrease in average per-person costs for members remaining on the Exchange. This effect is similar to the implementation of a high-risk pool.

MOTIVATION

Why revise Wyoming's original (2011) projections for Medicaid expansion? The simple answer is that experience from other expansion states has shown that actual enrollment has often exceeded original projections. This gap — between original projections[1] and actual enrollment[2] — is shown in Figure 1, below.

Figure 1: Gap between projected and actual enrollment, by state. Dark blue bars show actual enrollment, and light blue bars show original projections.

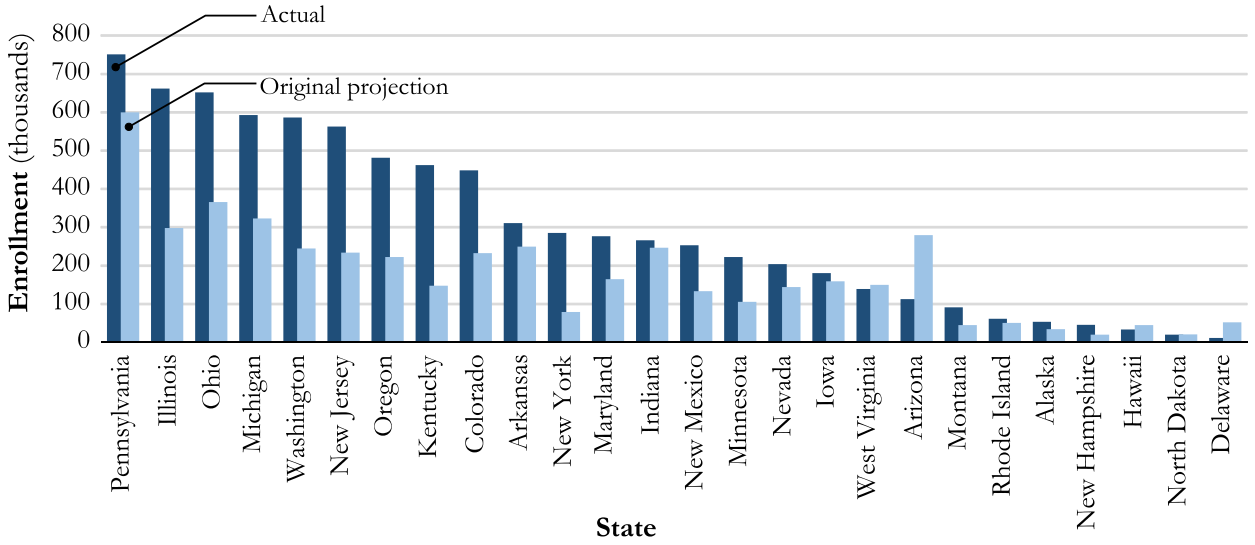


Figure 1 clearly demonstrates the need to thoroughly revise Wyoming's estimates of enrollment and costs, since many of the models used to estimate enrollment in these states may have been the same

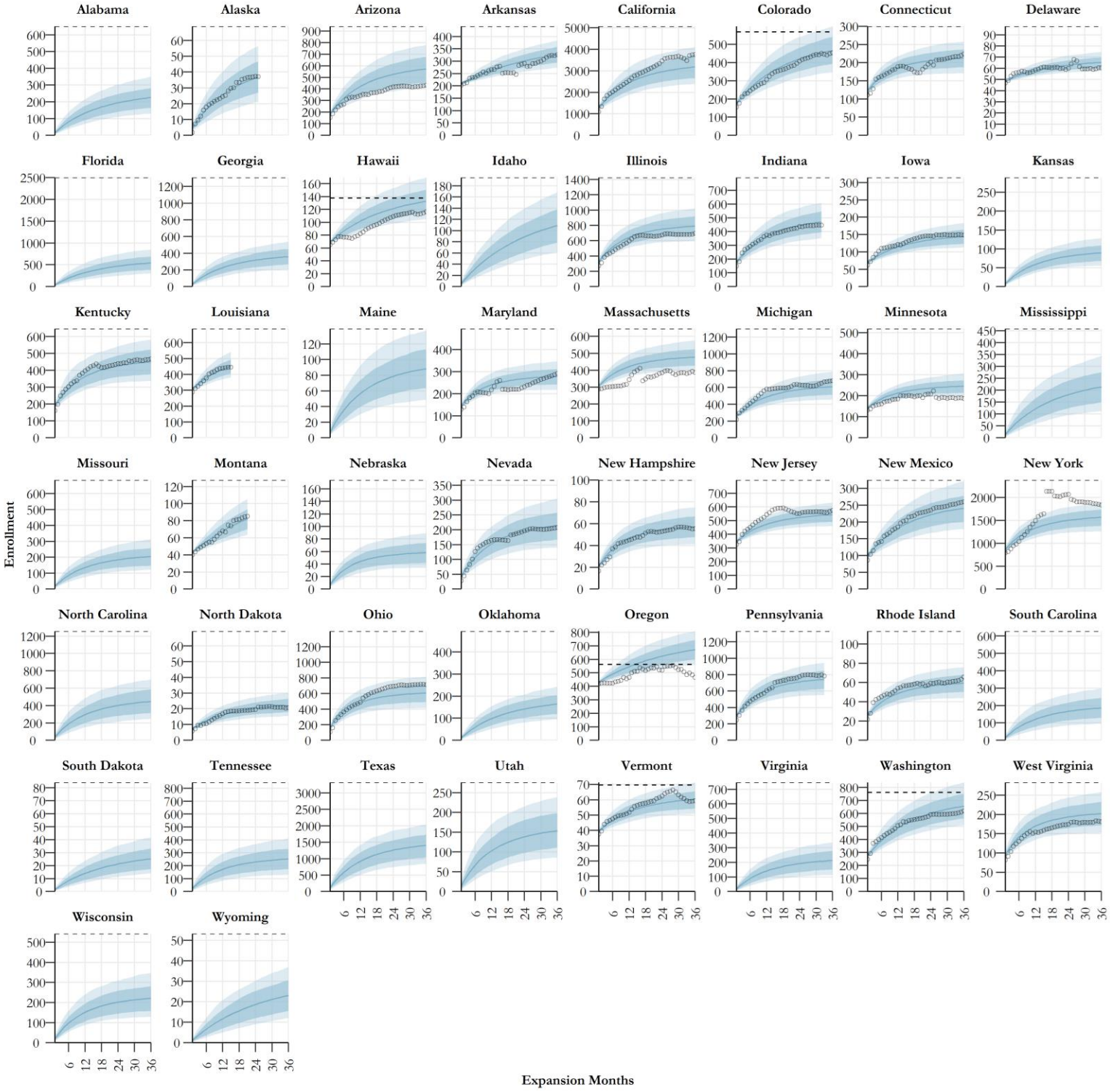
We do so using two important principals:

- 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.

As a comparison, our revised estimates are built off a statistical model that estimates overall enrollment *trajectories*, not just point estimates. Figure 2, on the next page, 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. Note that we excluded Massachusetts, Oregon, and New York from the model fitting due to their irregular trajectories — so the model understandably fits these states worse than the others.

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

Figure 2: Actual (black circles) vs. predicted (blue) enrollment trajectories and uncertainty

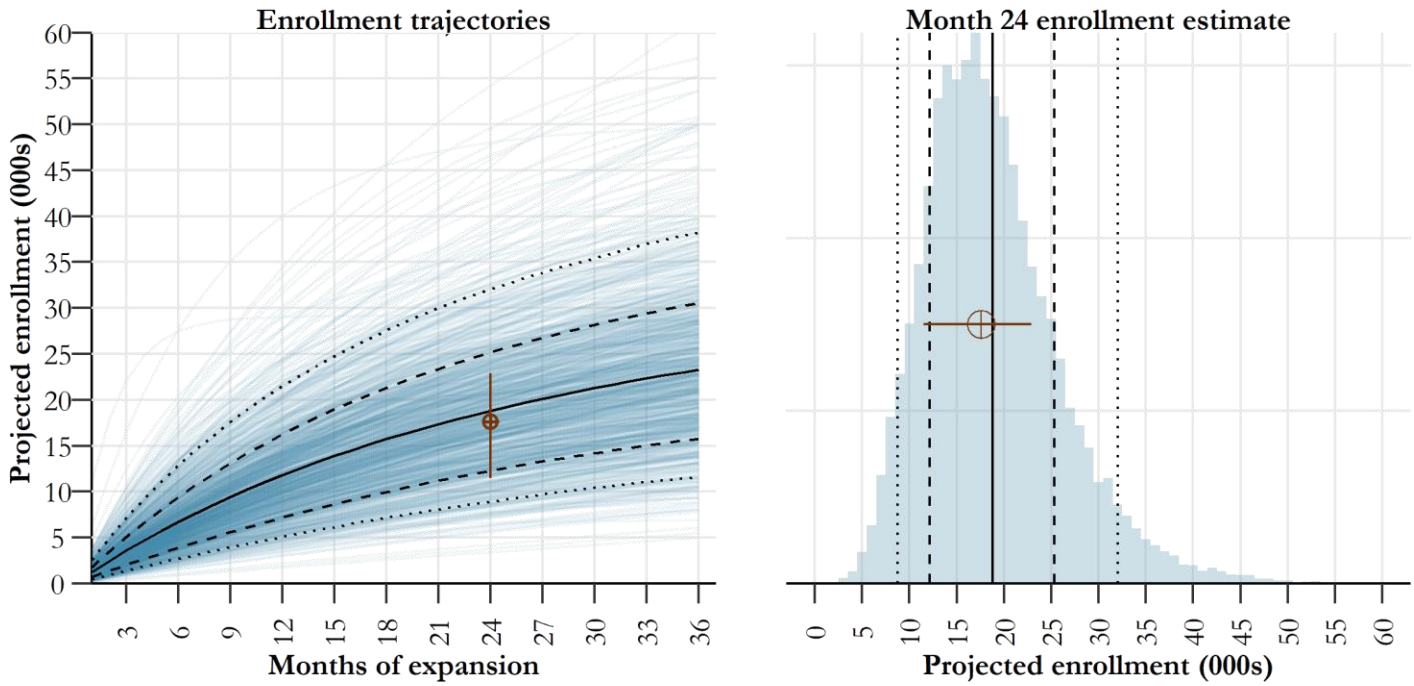


Enrollment and Costs

Enrollment

After two years (24 months), we expect Medicaid expansion enrollment to be at approximately 19,000 people, though the count is projected to grow for over subsequent years before plateauing. Figure 3, below, shows the significant range of uncertainty behind this 24-month snapshot (right) and in the overall trajectories out to 36 months (left).

Figure 3: Uncertainty in enrollment



On the figures, the blue histogram (right) and blue 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:

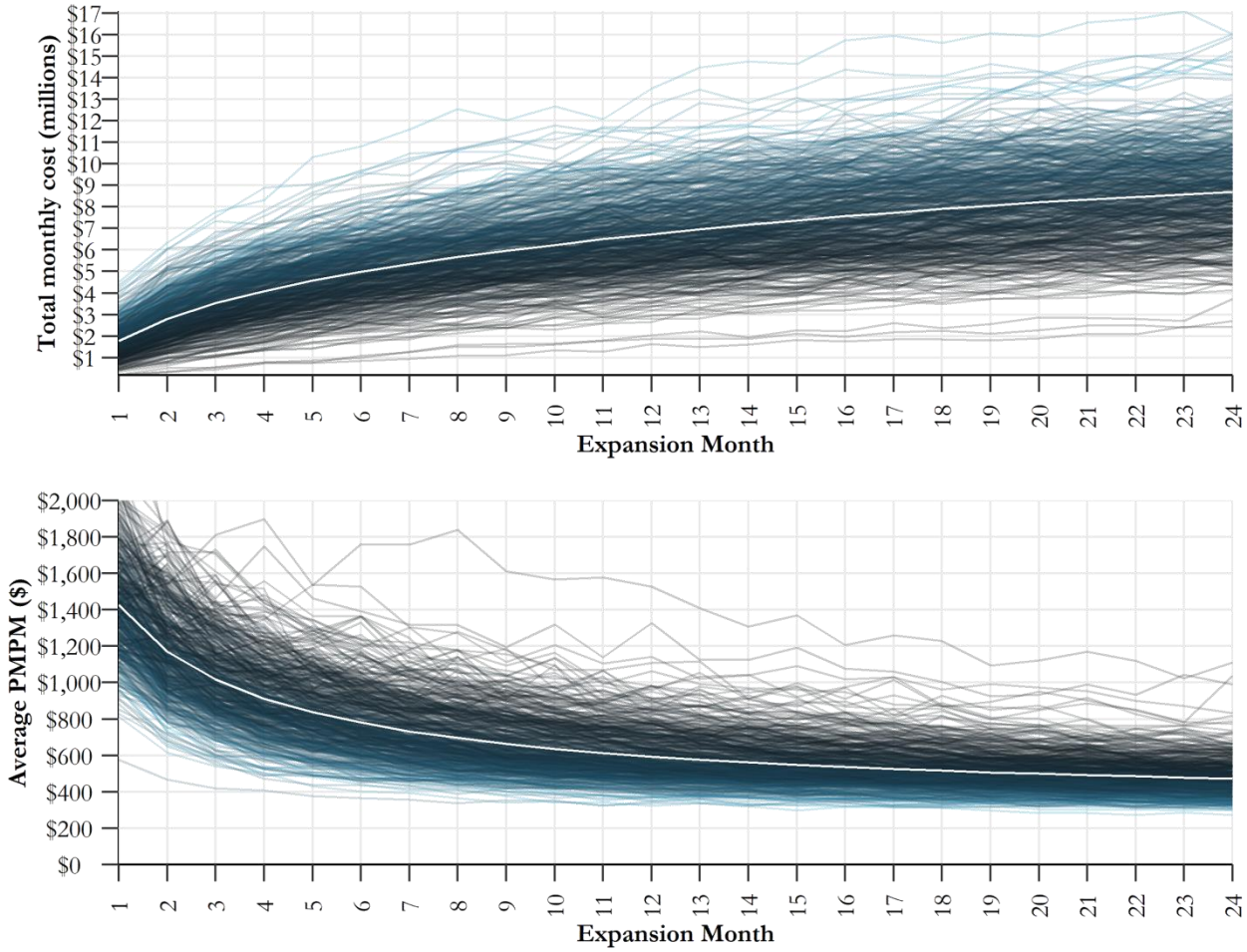
- Dashed lines represent 67% percentile (equal-tailed) intervals. This means that, working in from tails, 67% of potential scenarios lie between the dashed lines.
- Dotted lines show 90% percentile intervals.
- The brown circle and lines show estimates from Milliman (2011) and their "high" and "low" scenarios. Our estimates are roughly 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.

Costs

We project Medicaid medical and administrative costs for this population at ~$153 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 the most expensive.

This means that, in the world of this model, enrollment has an inverse relationship with per-member per month costs. In other words, if take-up is low, we anticipate the covered population to be sicker (and therefore more costly) than if take-up rate is high. Figure 4, 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 more intense shades of blue.

Figure 4: Projected monthly Medicaid expenditures (upper) and per-member per-month (PMPM) medical costs (lower). The white lines show expected values.

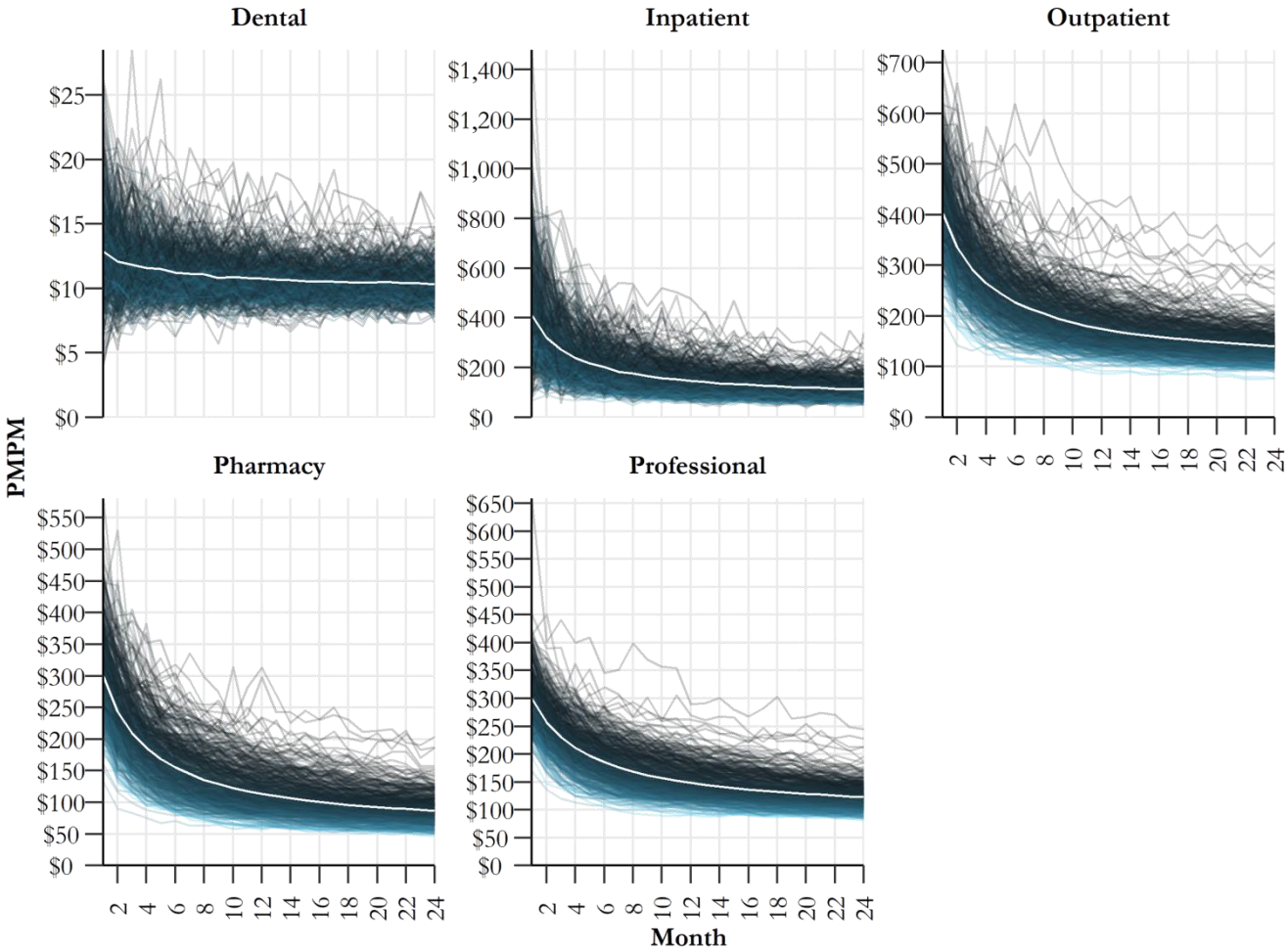


Note on the figure above that the expected total monthly costs at the end of the biennium are approximately $8.5 million. With no other information, this is the figure we would use to project costs for the next biennium.

Per-member per-month costs

Breaking down per-member per-month (PMPM) costs by claim type in Figure 5, below, we see a similar correlation between enrollment and PMPM — scenarios where we expect more enrollment will, generally speaking, have lower PMPM costs.

Figure 5: 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 1, on the next page, illustrates this breakdown of the total $153 million expected biennial cost. It tells us, for example, that we can expect in-State hospitals to receive ~$25.4 million in inpatient revenue and ~$22.3 million in outpatient revenue. Note, however, that crowd-out of private insurance (discussed in a subsequent section) does reduce net revenue received by all providers.

Table 1: 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[3]		Expected Expenditures	
			In-State	Out-of-State	In-State	Out-of-State
Dental	$2.8	Dental	96.6%	3.4%	$2.7	$0.1
Inpatient	$35.6	Hospital	71.3%	28.7%	$25.4	$10.2
Professional	$37.0	Ambulance	3.2%	0.4%	$1.2	$0.2
		Behavioral Health	19.2%	0.1%	$7.1	$0.0
		Dental	0.1%	0.0%	$0.0	$0.0
		Equipment / Supplies	3.2%	1.3%	$1.2	$0.5
		Laboratory/Imaging	4.2%	3.2%	$1.6	$1.2
		Other	11.4%	0.7%	$4.2	$0.3
		PT/OT	4.2%	0.1%	$1.6	$0.0
		Primary Care	17.8%	2.5%	$6.6	$0.9
		Specialist	24.6%	2.5%	$9.1	$0.9
		Vision	1.0%	0.2%	$0.4	$0.1
Outpatient	$43.0	Ambulatory Surgical Center	3.8%	0.1%	$1.6	$0.0
		Hospital	52.0%	4.4%	$22.3	$1.9
		Other	1.2%	0.4%	$0.5	$0.2
		PT/OT	0.1%	0.0%	$0.1	$0.0
		Primary Care	37.8%	0.3%	$16.2	$0.1
Pharmacy	$27.5	Pharmacy	83.1%	16.9%	$22.9	$4.6
Total medical	**$145.9**		85.4%	14.6%	**$124.6**	**$21.3**
Administrative	$7.3					
Total cost	**$153.2**					

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 pay not only for some State staff and infrastructure, but for all the marginal costs of processing additional claims and eligibility applications generated by the new members.

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

Required appropriation

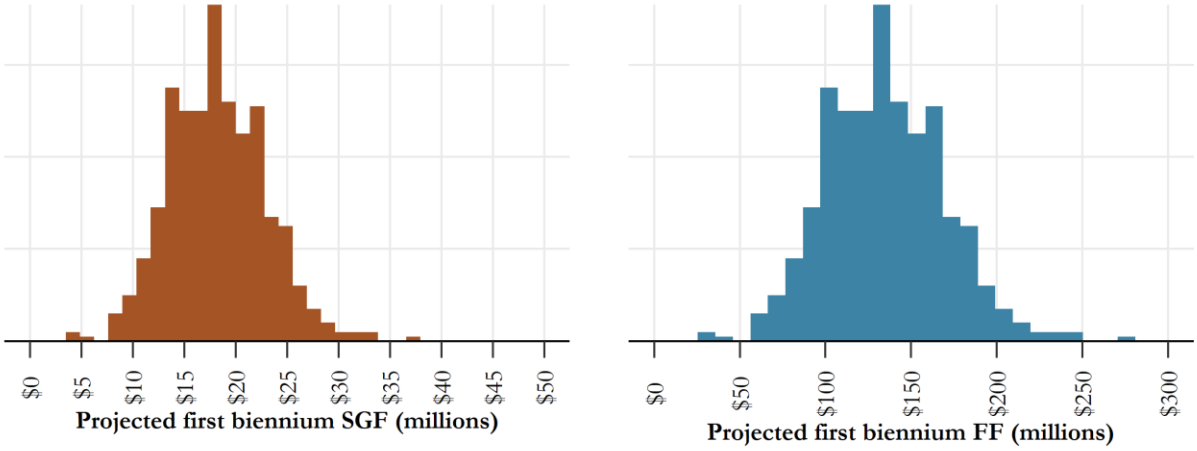
In order to translate these total costs into a potential appropriation recommendation, we make some adjustments:

- 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 a waiver, but the federal match could be as low as the usual 50%.

- The Federal government will match 50% of administrative expenditures.

Figure 6, below, shows the uncertainty in the State General Fund (SGF) and Federal Fund (FF) required expenditures for the first biennium.

Figure 6: Uncertainty in first biennium expenditures, by source



The uncertainty here is important. Our recommendation of $18 million SGF is based on the expected value, but there is non-negligible probability that actual SGF expenditures could be as high as $30 million.

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 enrollee based on available demographic data.

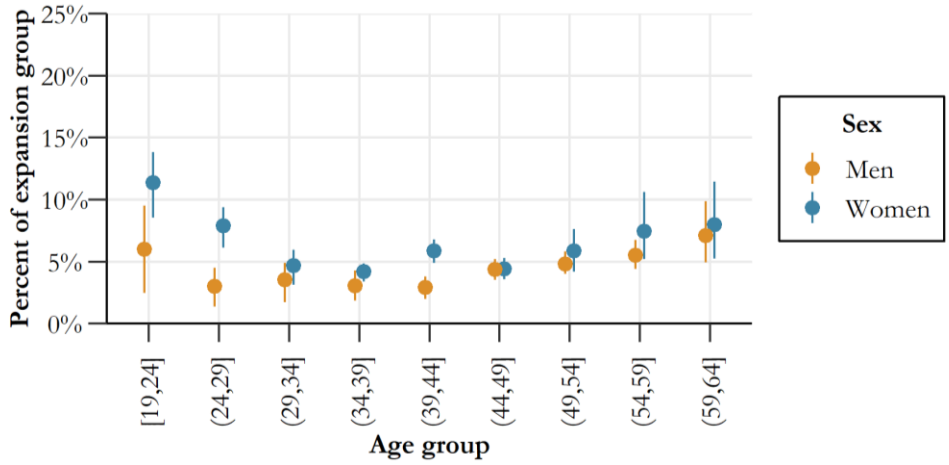
Demographics

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

- A group of younger (< 35 years old), predominantly female, enrollees, making up an estimated 36% (25 - 45%) of the total population.
- An older (over 50 years old) group of enrollees, making up an estimated 38% (29 - 50%) of the expansion group.

This bimodal distribution can be seen in Figure 7, below, where orange dots and ranges show estimates for men and blue dots and ranges show estimates for women.

Figure 7: Age and sex estimates

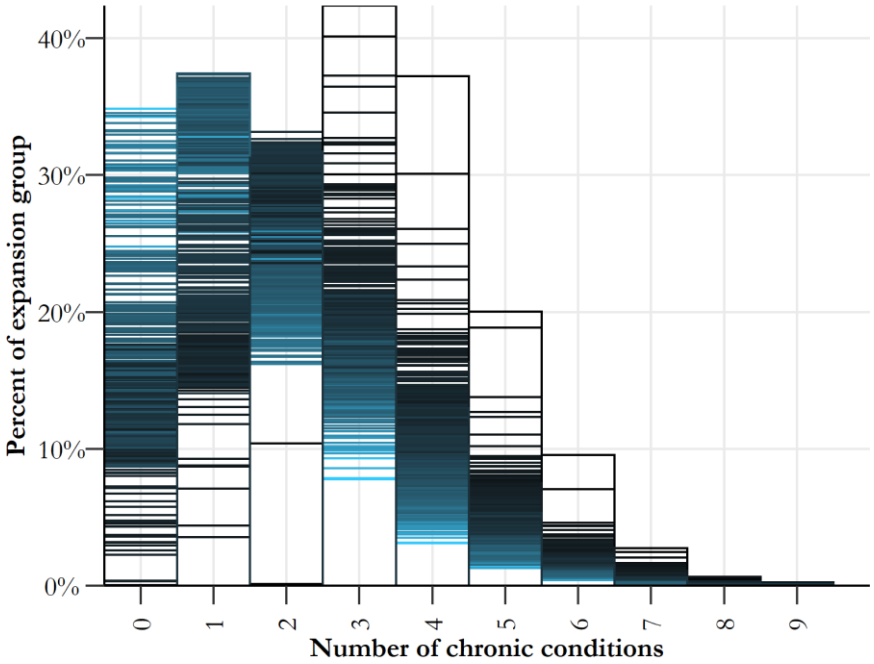


Health status

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 — because our model has sicker individuals enrolling first — 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 4.

Figure 8, on the next page, is a histogram showing the distribution of individuals by the estimated count of chronic conditions in the pool.

Figure 8: Count of chronic conditions by enrollment scenario (blue being higher enrollment, black being lower enrollment)



Note on the figure that higher enrollment scenarios (blue) have a distribution pushed further towards the left (fewer chronic conditions), whereas low-enrollment scenarios (black) have a fatter tail on the right.

Education

Table 2, below, shows the estimated education distribution of the expansion population. Note that the vast majority of people are high school graduates, and that most (56%) have at least some college education.

Table 2: Education status

Status	Estimate	95% Lower	95% Upper
No school	0.4%	0.2%	0.6%
Elementary	3.6%	2.6%	4.6%
Some high school	6.8%	5.5%	8.4%
High school graduate	33.4%	39.8%	37.0%
Some college	40.6%	37.5%	43.8%
College graduate	15.0%	11.9%	18.8%

Poverty level

We estimate that approximately two-thirds [59 - 67%] of enrollees will have incomes below 100% FPL; the other third will be between 100 - 138% FPL.

Employment and insurance coverage

Approximately half (43 - 57%) will be employed, 38% (33 - 46%) will not be in the labor force (e.g., retired or not looking for work), and 10% (9 - 12%) will be unemployed (and actively looking for work).

The distribution by age is shown in Figure 9, below. Generally speaking, we estimate that older individuals in the expansion will be less likely to be employed than younger enrollees.

Figure 9: Employment estimates

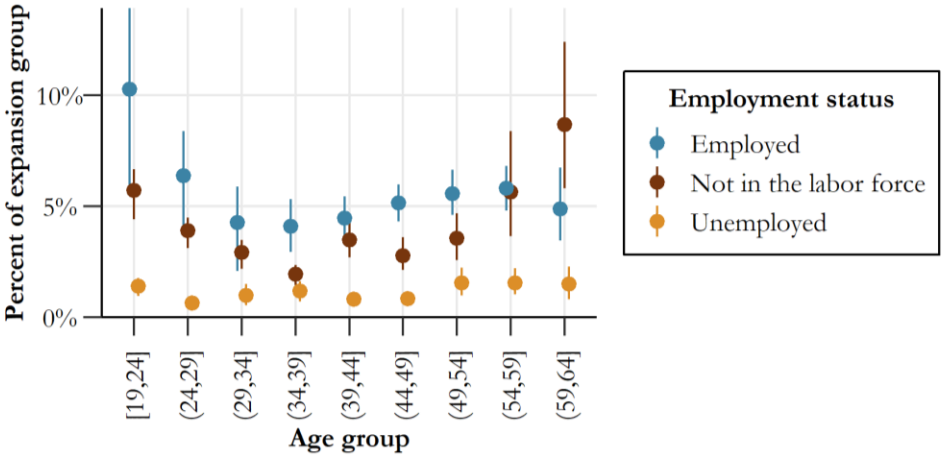
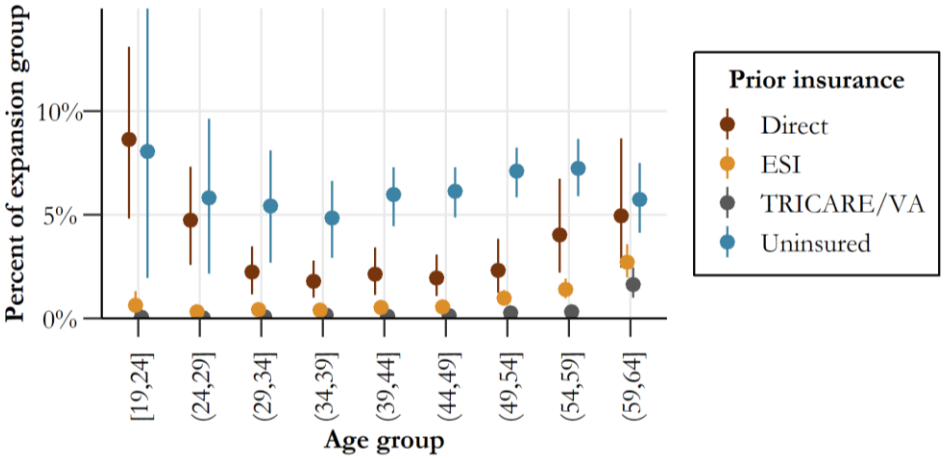


Figure 10, below, shows enrollees' prior insurance coverage (or lack thereof). Our estimate is that 56% (42 - 70%) of enrollees will have been previously uninsured, with the next largest fraction being the one-third (19 - 48%) that previously had directly-purchased insurance.

Figure 10: Prior insurance estimates



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.[4] 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 it offers the best chance to estimate causal effects without the problem of confounding variables.

(1) The first rigorous study was conducted in Oregon, which implemented a limited expansion of Medicaid in 2008. 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 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.
- 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.

[4] https://www.kff.org/medicaid/issue-brief/the-effects-of-medicaid-expansion-under-the-aca-updated-findings-from-a-literature-review-august-2019/

(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[5] 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 **~ 3 - 4 avoided deaths** for the approximately 6,055 (+/- 870) uninsured individuals between 45 and 64 in Wyoming below 138% FPL[6] over the next two years, **who would otherwise experience ~ 50 - 70 deaths** (an estimated baseline mortality rate of 1%) in the same period.

[5] 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
[6] American Community Survey 5-year PUMS (2012-16)

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 1 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 significantly lower than 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 between 100 - 400% of the Federal Poverty Level (FPL), and cost sharing reduction (CSR) subsidies are generally available between 100 - 250% FPL.[7]
- 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 and individuals above 400% FPL, who get absolutely nothing.

"Crowd-out" therefore means that — if Medicaid were expanded — individuals below 138% FPL on the Exchange would almost certainly drop their private plans and enroll in Medicaid. This is for three reasons:

- 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.
- 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.

[7] 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.

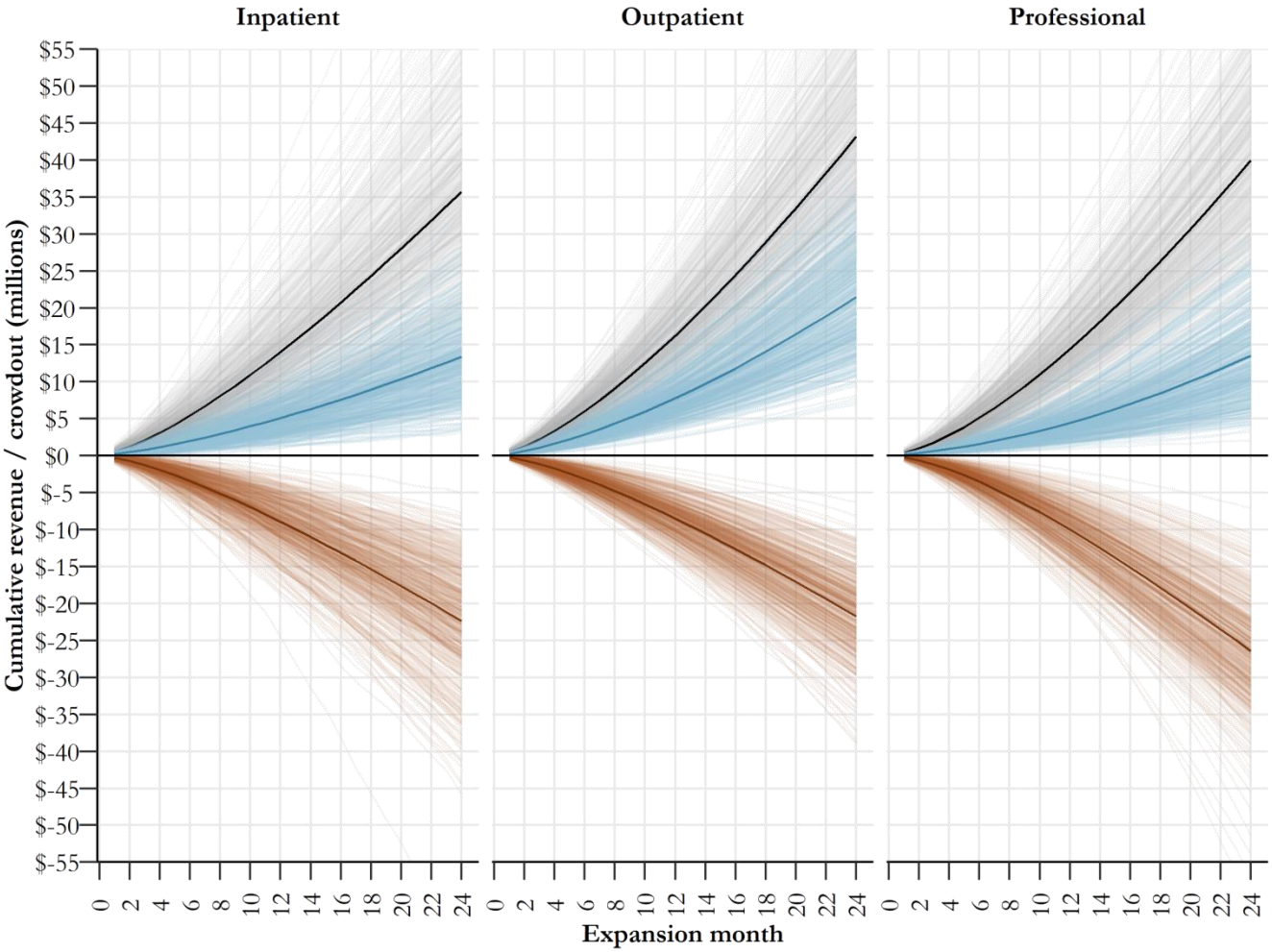
Some individuals covered by employer insurance will also move over to Medicaid, but this effect is less predictable (see the Methodology section for details on how crowd-out was implemented).

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.[8]

Figure 11, 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 11: New revenue (black), est. crowd-out (brown), and net revenue (blue)



[8] 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[9] experienced by those who were previously directly-insured or covered by employer-sponsored insurance in the simulation.

Table 3: 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 1 in the costs section.

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[9] 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 probable reduction in Exchange pool costs somewhere between 5 - 15% — though it must be noted that this is not a guaranteed outcome.

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%[10]; the same authors more recently estimated the impact on private insurance rates if Wisconsin were to expand Medicaid at 13 - 19%.[11]

- 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%.[12]

- The Kaiser Family Foundation estimates that states that expanded Medicaid had lower aggregate risk scores on their Exchange than states that did not.[13]

Using a Census-based simulation similar to the Medicaid expansion methodology, but restricted to the population of directly-insured individuals in Wyoming[14], 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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[10] 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

[11] 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/

[12] 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

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

[14] 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.

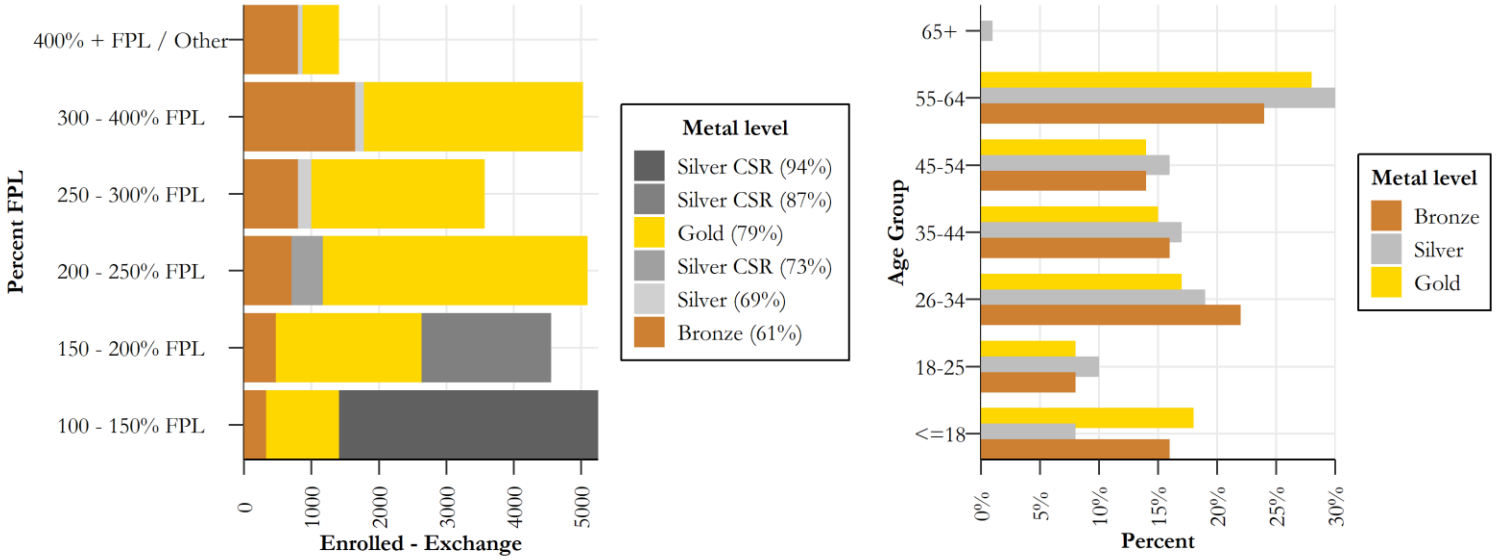
The first reason is the well-established correlation between income and health, known as the "income-health gradient."[15] On average, poorer people also tend to be sicker. So, without knowing anything else, it stands to reason that taking the poorest members of the Exchange out of the pool might improve the average health of the remaining covered lives.

The second reason is the evidence on plan selection from the Exchange itself (Figure 12, below), that provides two important takeaways:

- The closest analog to the Medicaid Expansion group (100 - 150% FPL) has largely bought the most generous plans available to them. 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.

- On the panel to the right, it's clear that people who buy Silver plans (i.e., the bottom two income groups, where CSR Silver variants are most prevalent) are largely older than those who buy Gold or Bronze plans (the upper income groups). Older people are generally sicker and more expensive to insure than younger people.

Figure 12: 2019 Marketplace plan selections by income and age group[16]



[15] A good summary can be found here: https://www.irp.wisc.edu/publications/focus/pdfs/foc301b.pdf
[16] 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

Alternative scenario

This outcome, however, is not guaranteed, and Wyoming's experience may vary from these national estimates. The primary insurer on the Exchange, Blue Cross Blue Shield (BCBS) notes, for example, that there is a reasonable possibility that the health status of the enrolled population at the higher income levels may actually be *worse* than that of the low-income population that would move to Medicaid, and thus some chance that the remaining risk pool post-expansion would be most costly than the current risk pool, resulting in higher rates for the non-subsidized individuals.

This is potentially due to the unique selection effects of significant federal premium subsidies (Advanced Premium Tax Credits) that mask the traditional income-health gradient on the Exchange by making the effective price of insurance for low-income individuals dramatically cheaper than for higher-income people. This lower effective price for the member means that healthier low-income individuals (with low or zero premiums) are more likely to enroll than healthier higher-income members.

BCBS also notes that the loss of individuals purchasing mostly Silver-level plans may also reduce the value of the "silver loading" strategy to the covered members that remain.

Note on selection effects

While there is no doubt that there is a selection effect caused by the subsidies, the Department believe that these effects are more likely to happen in much higher income levels (i.e., around the 400% FPL cliff, not near 138% FPL) because the premium tax credit subsidies ramp down gradually between 100% - 400% FPL before disappearing entirely.

As shown in Figure 11, the 100 - 150% group is only ~20% of the total Exchange population. The real question is therefore whether this bottom fifth is less healthy than the much larger 150 - 400% group above it that remains, not necessarily how the 100% - 400% group compares with the 400%+ group.

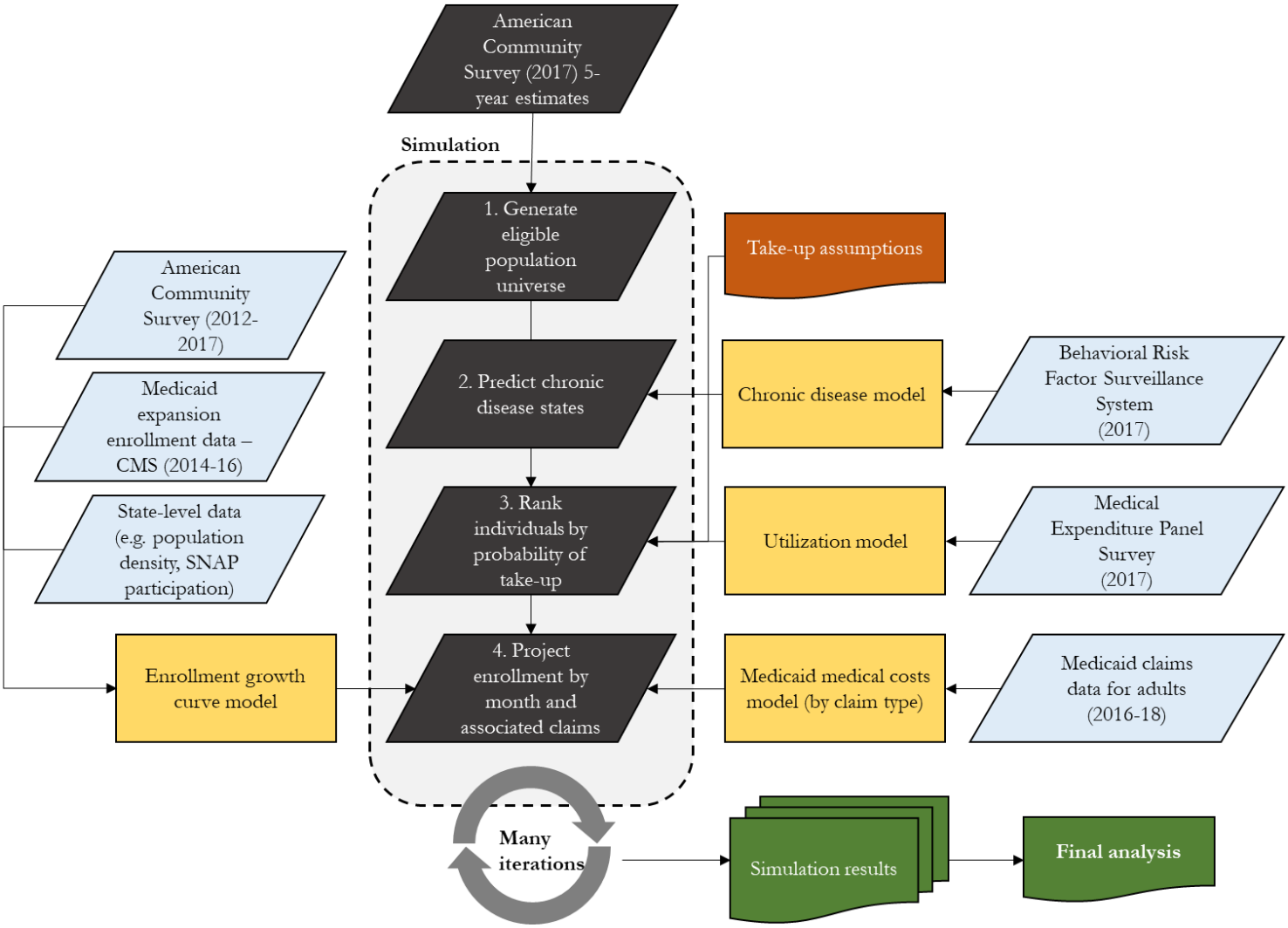
METHODOLOGY

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 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 13, 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 13: 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.[17] 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 56,533 in the 2017 5-year ACS data) and standard deviation (1,347) for this subset of people. We then draw a value from this (assumed normal) distribution to use as the eligible population count for each iteration of the simulation. 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. In this case, there are 2,591 observations in the survey data that are repeatedly expanded into some number between 54K and 58K "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 **total number of chronic conditions** (out of 10 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).

- Using the same demographic data plus the predicted number of chronic conditions, we then predict **expected (average) standardized[18] health care costs** for the simulated individuals using a model built off of 2017 Medical Expenditure Panel Survey (MEPS) data (Model 3, in the

[17] 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.

[18] 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.

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 two 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.[19]

    - 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.[20] 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.

(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

[19] This is based on the 20% coinsurance and approximate MOOP in the State Employees Group Insurance plan.
[20] 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.

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. Due to time restrictions, we ran 524 iterations of the simulation. This is adequate for the expected values and intervals presented in this document, but we'd likely need more iterations if we were, for example, to consider the tails more closely.

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 the Hamiltonian Monte Carlo "No U-Turn" Sampler in the Stan platform[21], with R statistical software and the brms package[22] as the interface. We used the data.table[23] and lubridate[24] packages to clean and process data, and the ggplot2[25] 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.

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.[26] 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

[21] Stan Development Team. 2018. RStan: the R interface to Stan. R package version 2.17.3. http://mc-stan.org
[22] 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>
[23] 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]
[24] 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/
[25] H. Wickham. ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2016.
[26] https://data.medicaid.gov/Enrollment/Medicaid-Enrollment-New-Adult-Group/pfrt-tr7q

later (Montana, Alaska, Louisiana). We then merge this state-level enrollment trajectory information (e.g., months of enrollment nested within states), with a variety of state-level predictors[27].

The trajectories are modeled as exponential decay, with enrollment starting at some initial level and growing more and more slowly to an asymptote defined by the Census estimate of the total eligible population times some take-up rate. We then estimate the takeup rate (tau) and growth rate (gamma) parameters as linear combinations of those state-level predictors, along with correlated regional and state-level varying intercepts.

```
Family: gaussian  Links: mu = identity; sigma = log
Formula: TotalAdult ~ StartingEnrollment + exp(tau) * DemoGroup * (1 - exp(-1 * exp(gamma) *
ExpansionMonths))
         tau ~ 1 + Econ2 + Estimate_INSURANCEESI + PHYSICALINACTIVITY + DENTALVISITANNUAL +
VIOLENTCRIME + HIGHHEALTHSTATUS + LogDens + (1 | region | Region) + (1 | regionstate |
Region:State)
         gamma ~ 1 + StartingFraction + +DRUGDEATHS + SUICIDE + HIGHHEALTHSTATUS + PctObama +
Estimate_EMPNILF + LogDens + (1 | region | Region) + (1 | regionstate | Region:State)
         sigma ~ 0 + log(DemoGroup)
   Data: model_dataset_pruned (Number of observations: 954)
Samples: 1 chains, each with iter = 20000; warmup = 1000; thin = 1;
         total post-warmup samples = 19000

Group-Level Effects:
~Region (Number of levels: 8)
                                    Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(tau_Intercept)                       0.25      0.16     0.02     0.61 1.00     6823     9461
sd(gamma_Intercept)                     0.20      0.16     0.01     0.59 1.00     8155    11272
cor(tau_Intercept,gamma_Intercept)     -0.23      0.43    -0.90     0.68 1.00    19128    14205

~Region:State (Number of levels: 28)
                                    Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(tau_Intercept)                       0.28      0.06     0.19     0.41 1.00    10460    12068
sd(gamma_Intercept)                     0.41      0.08     0.28     0.59 1.00     9149    12416
cor(tau_Intercept,gamma_Intercept)     -0.47      0.19    -0.78    -0.04 1.00    12509    13763

Population-Level Effects:
                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
tau_Intercept                -0.52      0.32    -1.14     0.10 1.00    15193    14582
tau_Econ2                     0.32      0.30    -0.28     0.90 1.00    14496    14741
tau_Estimate_INSURANCEESI    -0.58      0.81    -2.16     1.00 1.00    31511    14055
tau_PHYSICALINACTIVITY       -0.32      0.12    -0.55    -0.07 1.00    16364    13638
tau_DENTALVISITANNUAL        -0.12      0.11    -0.33     0.09 1.00    18102    14657
tau_VIOLENTCRIME             -0.10      0.07    -0.25     0.04 1.00    14339    13421
tau_HIGHHEALTHSTATUS         -0.26      0.13    -0.53    -0.01 1.00    12222    13836
tau_LogDens                  -0.07      0.05    -0.18     0.04 1.00    13604    13895
gamma_Intercept              -1.17      0.62    -2.35     0.06 1.00    23400    15614
gamma_StartingFraction       -0.65      0.58    -1.79     0.51 1.00    26072    14515
gamma_DRUGDEATHS              0.29      0.12     0.06     0.52 1.00    16014    14446
gamma_SUICIDE                -0.48      0.21    -0.90    -0.09 1.00    13706    13047
gamma_HIGHHEALTHSTATUS        0.13      0.12    -0.10     0.37 1.00    15998    14120
gamma_PctObama               -0.74      0.77    -2.25     0.77 1.00    33196    15079
gamma_Estimate_EMPNILF       -0.94      0.92    -2.73     0.87 1.00    39528    12976
gamma_LogDens                -0.12      0.12    -0.36     0.11 1.00    14451    13668
sigma_logDemoGroup            0.70      0.00     0.70     0.70 1.00    15520    10544
```

[27] These include: data from America's Health Rankings, Census and SAHIE, estimates on insurance coverage, OES data on state-level employment by sector and Wikipedia data on the 2012 election. Other sources (e.g. SNAP enrollment) were included in earlier models.

2. Chronic disease count model

This model draws upon Wyoming Behavioral Risk Factor Surveillance System (BRFSS) microdata to estimate the total count of 10 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;
- Skin cancer;
- Other cancer.

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

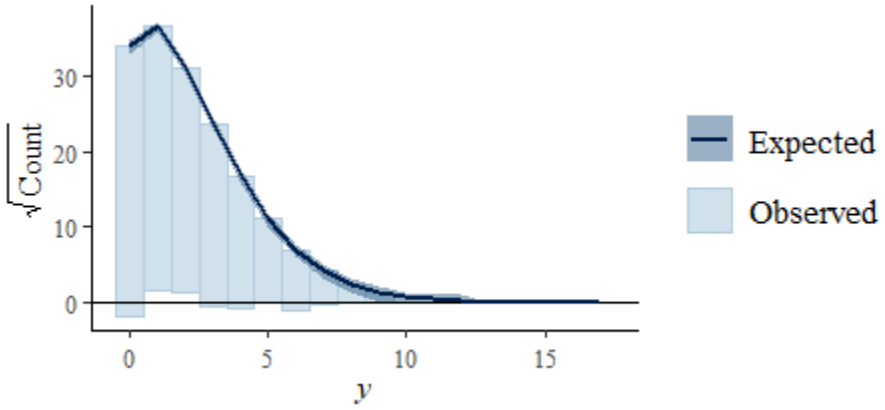
```
Family: poisson
  Links: mu = log
Formula: Chronic ~ 1 + s(zAge, by = MALE) + RACE + OWNRENT + VETERAN + EMPLOYMENT + INCOME +
INSURANCE + (1 | IMONTH) + (1 | INTVID) + (1 | COUNTY)
   Data: wy_2017_subset (Number of observations: 4463)
Samples: 4 chains, each with iter = 3000; warmup = 1000; thin = 1;
         total post-warmup samples = 8000

Smooth Terms:
                  Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(szAgeMALE0_1)     0.85      0.31     0.40     1.60 1.00     4568     5593
sds(szAgeMALE1_1)     0.85      0.35     0.37     1.72 1.00     4248     5854

Group-Level Effects:
~COUNTY (Number of levels: 23)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.07      0.02     0.03     0.11 1.00     3372     3618

~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     4289     3731

~INTVID (Number of levels: 424)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.06      0.03     0.01     0.11 1.00     1374     1999

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

Intercept	0.63	0.12	0.39	0.86	1.00	4770	5920
RACEAsian	-0.30	0.32	-0.95	0.31	1.00	10917	5819
RACEBlack	-0.20	0.19	-0.57	0.16	1.00	7142	5851
RACEHispanic	-0.04	0.12	-0.26	0.19	1.00	4433	5855
RACEOther	0.00	0.14	-0.26	0.27	1.00	5107	6497
RACEWhite	-0.07	0.10	-0.27	0.14	1.00	4134	5428
OWNRENT	-0.23	0.03	-0.30	-0.17	1.00	11243	5982
VETERAN	0.04	0.03	-0.03	0.11	1.00	13607	5843
EMPLOYMENTNILF	0.31	0.03	0.25	0.37	1.00	12369	6710
EMPLOYMENTUnemployed	0.25	0.06	0.13	0.37	1.00	13951	6623
INCOME25K	-0.12	0.05	-0.22	-0.02	1.00	4327	5753
INCOME35K	-0.21	0.06	-0.32	-0.09	1.00	4524	5572
INCOME50K	-0.26	0.05	-0.36	-0.15	1.00	4285	5867
INCOME50Kplus	-0.39	0.05	-0.49	-0.29	1.00	3706	5660
INCOMEOther	-0.39	0.05	-0.49	-0.28	1.00	4461	6271
INSURANCE	0.14	0.05	0.04	0.23	1.00	14550	6007
szAge:MALE0_1	0.56	0.82	-1.09	2.11	1.00	6128	5321
szAge:MALE1_1	1.09	0.85	-0.66	2.68	1.00	6647	5668

Figure 14, below, shows the distribution of chronic disease counts in the survey data, compared with the expected distribution resulting from the model. Note that this model has two minor problems, which could be improved in future iterations:

- It slightly under-predicts the actual amount of zeros in the data;
- It puts a small amount of probability mass on counts above 10, which do not exist in this construct.

Figure 14: Posterior predictive hanging rootogram of count of chronic conditions



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 are 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: I ~ 1 + Male * zAge + zChronic + (1 | ID)
         hu ~ 1 + Male * zAge + zChronic + (1 | id | ID)
         O ~ 1 + Male * zAge + zChronic + (1 | ID)
         hu ~ 1 + Male * zAge + zChronic + (1 | id | ID)
         M ~ 1 + Male * zAge + zChronic + (1 | ID)
         hu ~ 1 + Male * zAge + zChronic + (1 | id | ID)
         P ~ 1 + Male * zAge + zChronic + (1 | ID)
         hu ~ 1 + Male * zAge + zChronic + (1 | id | ID)
         D ~ 1 + Male * zAge + zChronic + (1 | ID)
         hu ~ 1 + Male * zAge + zChronic + (1 | id | ID)
   Data: model_dataset (Number of observations: 15879)
Samples: 4 chains, each with iter = 6000; warmup = 1000; thin = 1;
         total post-warmup samples = 20000

Group-Level Effects:
~ID (Number of levels: 1744)
```

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sd(I_Intercept)	0.44	0.20	0.03	0.78	1.01	1700	3666
sd(hu_I_Intercept)	1.41	0.20	1.04	1.83	1.00	1820	6425
sd(hu_O_Intercept)	1.62	0.06	1.50	1.74	1.00	9244	12748
sd(hu_M_Intercept)	1.62	0.05	1.52	1.73	1.00	9096	12325
sd(hu_P_Intercept)	2.17	0.07	2.04	2.31	1.00	7717	10868
sd(hu_D_Intercept)	1.44	0.10	1.26	1.64	1.00	6357	10560
sd(O_Intercept)	0.81	0.03	0.75	0.88	1.00	7136	12394
sd(M_Intercept)	0.57	0.02	0.52	0.61	1.00	9227	13467
sd(P_Intercept)	1.21	0.03	1.15	1.27	1.00	3742	7820
sd(D_Intercept)	0.22	0.11	0.02	0.43	1.00	2522	4449
cor(hu_I_Intercept,hu_O_Intercept)	0.73	0.08	0.56	0.87	1.02	286	650
cor(hu_I_Intercept,hu_M_Intercept)	0.75	0.07	0.59	0.89	1.01	230	279
cor(hu_O_Intercept,hu_M_Intercept)	0.71	0.02	0.66	0.76	1.00	7571	12817
cor(hu_I_Intercept,hu_P_Intercept)	0.49	0.09	0.30	0.66	1.01	277	424
cor(hu_O_Intercept,hu_P_Intercept)	0.64	0.03	0.58	0.69	1.00	5819	10436
cor(hu_M_Intercept,hu_P_Intercept)	0.79	0.02	0.76	0.82	1.00	7406	12966
cor(hu_I_Intercept,hu_D_Intercept)	0.25	0.14	-0.02	0.51	1.01	357	828
cor(hu_O_Intercept,hu_D_Intercept)	0.29	0.06	0.18	0.41	1.00	10725	15636
cor(hu_M_Intercept,hu_D_Intercept)	0.38	0.05	0.28	0.48	1.00	12809	15613
cor(hu_P_Intercept,hu_D_Intercept)	0.40	0.05	0.30	0.50	1.00	12920	16354

```
Population-Level Effects:
```

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
I_Intercept	8.89	0.16	8.58	9.21	1.00	21787	16667
hu_I_Intercept	4.90	0.27	4.41	5.47	1.00	1422	6191
O_Intercept	5.74	0.07	5.61	5.88	1.00	8621	12871
hu_O_Intercept	0.49	0.11	0.27	0.71	1.00	10158	13361
M_Intercept	5.42	0.05	5.33	5.51	1.00	11171	14363
hu_M_Intercept	-0.69	0.11	-0.90	-0.48	1.00	9080	12413
P_Intercept	4.57	0.08	4.41	4.73	1.00	2558	5717
hu_P_Intercept	-1.41	0.15	-1.69	-1.12	1.00	9779	13055
D_Intercept	5.04	0.09	4.86	5.21	1.00	31497	16373
hu_D_Intercept	3.63	0.16	3.33	3.95	1.00	14340	15565
I_Male	0.14	0.20	-0.24	0.53	1.00	22310	15625
I_zAge	0.35	0.26	-0.16	0.86	1.00	18640	15931
I_zChronic	-0.01	0.14	-0.28	0.26	1.00	13667	14296

I_Male:zAge	-0.09	0.38	-0.84	0.65	1.00	20079	16899
hu_I_Male	-0.24	0.25	-0.73	0.25	1.00	21402	16517
hu_I_zAge	0.37	0.35	-0.32	1.06	1.00	13992	14891
hu_I_zChronic	-1.62	0.22	-2.05	-1.19	1.00	6825	11333
hu_I_Male:zAge	-0.62	0.50	-1.61	0.35	1.00	16033	15356
O_Male	0.05	0.08	-0.10	0.20	1.00	9507	13620
O_zAge	0.39	0.10	0.20	0.58	1.00	8437	12314
O_zChronic	0.28	0.07	0.15	0.41	1.00	8846	12984
O_Male:zAge	-0.33	0.15	-0.63	-0.04	1.00	9419	12128
hu_O_Male	0.48	0.11	0.27	0.69	1.00	10413	14088
hu_O_zAge	0.25	0.14	-0.02	0.52	1.00	7979	12173
hu_O_zChronic	-1.76	0.10	-1.97	-1.56	1.00	8391	12484
hu_O_Male:zAge	-0.25	0.20	-0.64	0.15	1.00	9544	13112
M_Male	-0.05	0.05	-0.14	0.05	1.00	12025	14856
M_zAge	0.16	0.07	0.03	0.29	1.00	10231	13725
M_zChronic	0.27	0.05	0.19	0.36	1.00	10729	14280
M_Male:zAge	-0.03	0.10	-0.23	0.17	1.00	11032	14208
hu_M_Male	0.61	0.10	0.42	0.81	1.00	9499	12649
hu_M_zAge	0.27	0.13	0.01	0.54	1.00	7510	11985
hu_M_zChronic	-1.95	0.10	-2.15	-1.76	1.00	8275	12726
hu_M_Male:zAge	-0.17	0.19	-0.55	0.20	1.00	8439	12221
P_Male	-0.07	0.09	-0.24	0.10	1.00	3052	5388
P_zAge	0.42	0.11	0.21	0.63	1.00	2944	6374
P_zChronic	0.69	0.07	0.54	0.84	1.00	2657	5592
P_Male:zAge	-0.14	0.17	-0.48	0.19	1.00	3143	6377
hu_P_Male	0.79	0.13	0.54	1.05	1.00	10358	13065
hu_P_zAge	0.09	0.17	-0.25	0.42	1.00	7346	11145
hu_P_zChronic	-2.51	0.13	-2.78	-2.26	1.00	8334	11681
hu_P_Male:zAge	-0.71	0.25	-1.20	-0.23	1.00	8156	12633
D_Male	0.20	0.09	0.02	0.39	1.00	30335	16576
D_zAge	-0.18	0.11	-0.40	0.04	1.00	21928	16158
D_zChronic	-0.08	0.08	-0.25	0.08	1.00	27310	16423
D_Male:zAge	-0.12	0.17	-0.46	0.22	1.00	22830	15607
hu_D_Male	0.25	0.14	-0.03	0.52	1.00	16883	16435
hu_D_zAge	0.44	0.18	0.08	0.80	1.00	12421	15030
hu_D_zChronic	-0.62	0.13	-0.88	-0.37	1.00	13946	14235
hu_D_Male:zAge	-0.62	0.27	-1.15	-0.10	1.00	14262	14293

Family Specific Parameters:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma_I	0.76	0.12	0.53	0.98	1.01	2056	5287
sigma_O	1.07	0.02	1.04	1.11	1.00	17614	15334
sigma_M	1.02	0.01	0.99	1.04	1.00	23069	15214
sigma_P	0.92	0.01	0.90	0.94	1.00	23784	15883
sigma_D	0.93	0.04	0.85	1.00	1.00	5500	11237

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
```