

# KNG Health Reform Model: Technical Report

*Version 1.2*

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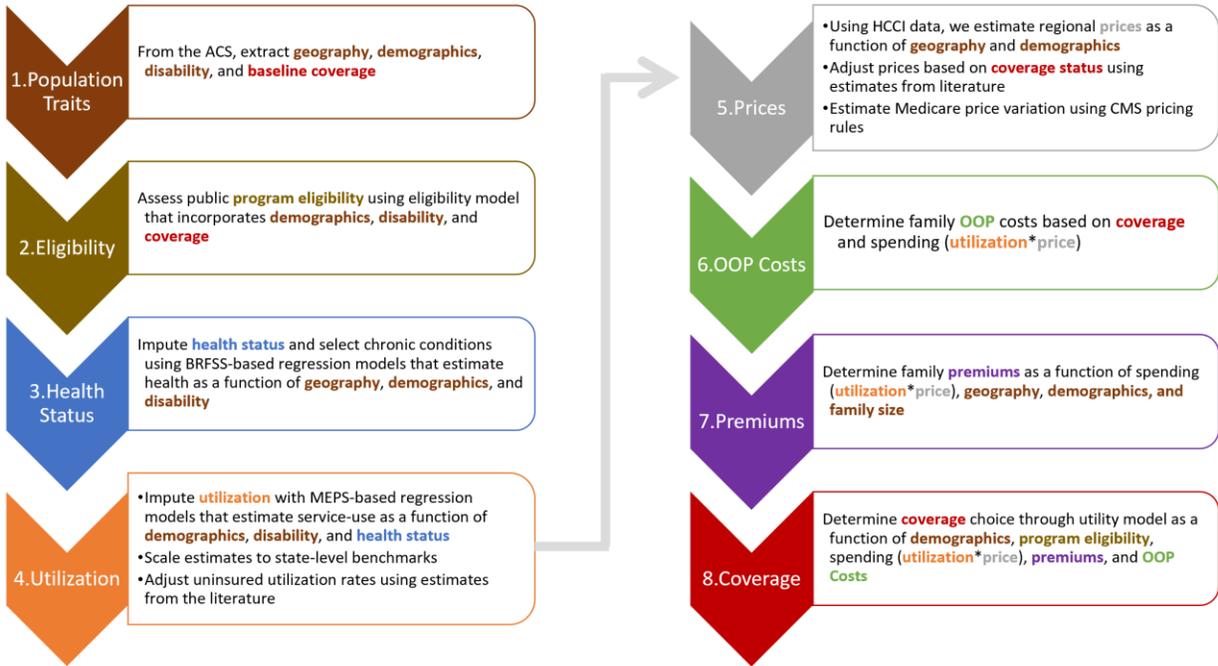


## Introduction

The KNG Health Reform Model (KNG-HRM) is a microsimulation model that can estimate the impact of comprehensive health reform proposals on health coverage and expenditures. The design of the model was informed by studying similar models that have been developed by the Congressional Budget Office (CBO), the Urban Institute, RAND Corporation, and the Lewin Group.

The model starts with a nationally representative sample of households from the American Community Survey (ACS) and proceeds to simulate coverage by moving through eight distinct modules. These modules are summarized in Figure 1. Coverage choices incorporate program eligibility, expected consumption, insurance premiums, expected out-of-pocket costs (OOP), risk, and demographic characteristics. The model is iterative, with health insurance premiums updating in response to changing risk pool compositions and model agents reselecting coverage until an equilibrium is reached.

**Figure 1. Overview of the eight Modules included within the KNG-HRM**



The model is designed to forecast coverage levels, utilization by service category (e.g. hospitalizations, outpatient visits, etc.), spending by service category, insurance premiums, and select components of public spending under a large variety of policy scenarios. These model outputs can be generated over extended time horizons and can be summarized at either the national or the local level. In the subsequent sections, we describe our approach for implementing each module.

## Module 1: Population Traits

### Overview

We construct an American Community Survey (ACS) data extract that provides a nationally representative sample of U.S. families for every year between 2018 and 2033. We develop our ACS data extract by following these three steps:

1. We create an ACS data extract that is limited to minors and non-incarcerated non-elderly adults without public insurance coverage.
2. We develop a population projection file that combines national projections from the U.S. Census with state-specific projections released by individual state governments.
3. For each year to be projected, we update the population weights in our ACS data extract to reflect changes in the composition of the U.S. population.

### Data

#### American Community Survey (ACS)

The ACS is a large annual household survey conducted by the U.S. Census Bureau (U.S. Census).<sup>1</sup> We obtained the 2017 ACS from the IPUMS website.<sup>2</sup> The file includes three million respondents spread over more than one million households. We relied on a variety of information from the file, including:

- Geography: State and Public Use Microdata Area (PUMA)<sup>3</sup>;
- Demographics: Age, Sex, Race, Ethnicity;
- Insurance coverage status (e.g. covered by employer, Medicaid, uninsured, etc.)
- Relationships to other members of the household;
- Employment status, industry, and occupation;
- Income by source;
- Education; and
- Disability status (e.g. vision, hearing, ambulation, cognitive, self-care, and independent living)

The ACS is the primary data source used in the KNG-HRM.

#### U.S. Census Population Projections

The U.S. Census provides national population estimates by single year of age, sex, race, and Hispanic origin for the years 2017z to 2060.<sup>4</sup>

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<sup>1</sup> American Community Survey. United States Census Bureau. 2017. Available at <https://bit.ly/1M2wMJQ>.

<sup>2</sup> Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. IPUMS USA: Version 8.0 [dataset]. Minneapolis, MN: IPUMS, 2018. <https://doi.org/10.18128/D010.V8.0>

<sup>3</sup> PUMAs are a custom geographic unit developed by the U.S. Census. PUMAs are defined as collections of counties or census tracts. PUMAs do not cross state lines. There are 2,351 PUMAs and each PUMA contains between 100,000 and 300,000 people.

<sup>4</sup> 2017 National Population Projections Datasets. United States Census Bureau. 2017. Available at <https://bit.ly/2EeZlm7>.

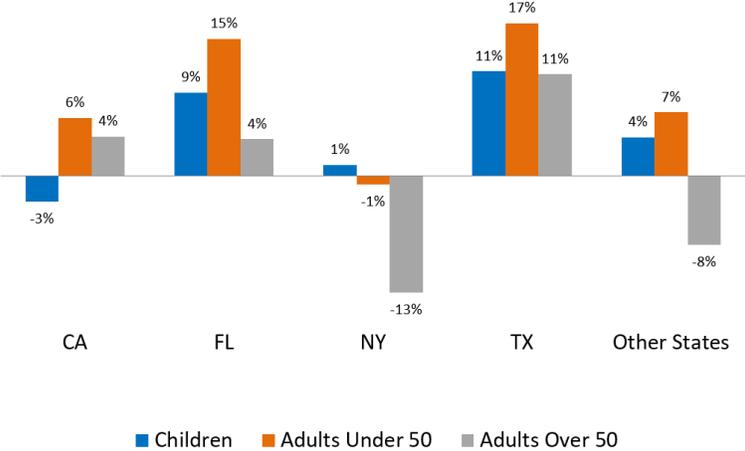
State-Based Population Projections

For twelve states (including California, Texas, Florida, and New York), we supplemented the U.S. Census demographic projections with additional state-specific population projections published by individual state governments. Links to these additional state-based projections are provided in Figure 2. State-based projections were included to account for national population trends not necessarily being applicable in all regions due to distinctive regional factors (e.g. immigration). Figure 3 shows how our projections for aggregate 2018-2033 population growth vary across states.

**Figure 2. Sources for State-Based Population Projections**

State	Source	Link
Arizona	Maricopa Association of Governments	<a href="https://bit.ly/2loHrI4">https://bit.ly/2loHrI4</a>
California	State of California Dep. Of Finance	<a href="https://bit.ly/2ITfNRd">https://bit.ly/2ITfNRd</a>
Colorado	Colorado Information Marketplace	<a href="https://bit.ly/2xKP0OS">https://bit.ly/2xKP0OS</a>
Delaware	Delaware Office of State Planning Coordination	<a href="https://bit.ly/2zCzTYZ">https://bit.ly/2zCzTYZ</a>
Florida	University of Florida BEBR	<a href="https://bit.ly/2DLmeTo">https://bit.ly/2DLmeTo</a>
Iowa	State Data Center of Iowa	<a href="https://bit.ly/2xZmKXS">https://bit.ly/2xZmKXS</a>
Minnesota	Minnesota State Demographic Center	<a href="https://bit.ly/2iICzwN">https://bit.ly/2iICzwN</a>
New York	New York State Department of Labor	<a href="https://on.ny.gov/2QcXJA3">https://on.ny.gov/2QcXJA3</a>
North Carolina	North Carolina Department of Budget and Management	<a href="https://bit.ly/2Qfzd14">https://bit.ly/2Qfzd14</a>
Tennessee	University of Tennessee Boyd Center	<a href="https://bit.ly/2OlivUU">https://bit.ly/2OlivUU</a>
Texas	Texas Demographic Center	<a href="https://bit.ly/2NO2Tpy">https://bit.ly/2NO2Tpy</a>
Utah	University of Utah Policy Institute	<a href="https://bit.ly/2DBYcp6">https://bit.ly/2DBYcp6</a>

**Figure 3. Aggregate projected population growth between 2018 and 2033 by state**



Exclusions

We apply the following exclusions to our ACS sample:

- We exclude respondents aged 65 and older.
- We exclude respondents under age 50 who reside in institutionalized group quarters, under the assumption that these respondents are incarcerated.
- We exclude respondents covered by Medicare, TRICARE, Indian Health Services, or Veterans benefits.

Thus, our sample includes all minors and non-incarcerated non-elderly adults without public insurance coverage.

### Constructing a Population Projection File

To create state-level population projections, we began with the U.S. Census Population Projections, which were specific to age, sex, and race, but not state. We then supplemented this file with additional state-based population projections. We were unable to find projections for all states, and many states presented projections in a manner that was difficult for us to incorporate. Ultimately, we included projections for states that were either highly populated (e.g. California, Texas, Florida, and New York) or whose projections were presented similarly to a highly populated state, and thus were relatively straightforward to incorporate. Even still, many of the state-based projections were presented differently. For example, some projections were provided for every year, while others generated in multiyear time increments. For each state, we combined information from the state and the national projections to fill in gaps and generate complete projection datasets.

### Projecting the ACS File Forward

We used our population projection growth rates to develop annual growth rates by year for each single year of age, sex, race, and ethnicity combination. We projected the 2017 ACS forward by linking each respondent to the appropriate growth rate and multiplying this growth rate by their population weight.

## Module 2: Eligibility

### Overview

We assess eligibility for Medicaid and federal subsidies on the state Health Insurance Marketplaces through consideration of family income, pregnancy status, disability status, and documentation status. Our methodology for assessing eligibility follows five steps:

1. We estimate each family's ratio of modified adjusted gross income to the federal poverty level.
2. We impute pregnancy status for female respondents of child-bearing age.
3. We impute documentation status for foreign-born respondents.
4. We assess Medicaid eligibility by comparing family income to state-specific eligibility thresholds.
5. We calculate the premium cap used for determining Marketplace subsidies.

### Data

#### Medicaid/CHIP Eligibility Limits

The Kaiser Family Foundation (KFF) publishes state-specific income eligibility thresholds for children, parents, pregnant women, and other adults.<sup>5</sup> These thresholds can be compared with family income levels to assess Medicaid eligibility.

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<sup>5</sup> Trends in Medicaid Income Eligibility Limits. Kaiser Family Foundation. <https://bit.ly/2Gpp29q>.

### U.S. unauthorized immigrant population estimates by state

The Pew Research Center (Pew) publishes state-specific estimates for the percent of the foreign-born population that is unauthorized.<sup>6</sup> We use these estimates to simulate documentation status, which has implications for public program eligibility.

### Approach

Not all coverage options are available to all people. For example, only certain people are eligible to enroll in Medicaid or receive premium subsidies on the Health Insurance Marketplaces (the Exchanges). Eligibility for these programs is determined based on modified adjusted gross income (MAGI) for the family. We approximate MAGI in the ACS by using the following formula:

$$\begin{aligned} \text{MAGI} = & \text{Wage and Salary Income} \\ & + 92.35\% \text{ of Business and Farm Income} \\ & + \text{Interest, dividend, and rental income} \\ & + \text{Retirement Income} \\ & + \text{Social Security Income} \end{aligned}$$

We defined families using a modified version of the Health Insurance Unit (HIU) Stata program released by the State Health Access Data Assistance Center (SHADAC), and summed MAGI for the entire family.<sup>7</sup> Income for family members under age 16 was excluded. Each family's MAGI was divided by the Federal Poverty Level (FPL) to determine the family's FPL ratio. These thresholds determined Medicaid eligibility, exchange premium subsidies, and eligibility for cost-sharing reduction plans on the exchanges.

The ACS does not report pregnancy status, but female respondents do report fertility (i.e. whether they had a child in the prior year). We used a logistic regression with state fixed effects to predict fertility in the ACS as a function of age, race, and ethnicity. Using this model, we predicted a fertility rate for each female respondent in the ACS between the ages of 19 and 45. We reduced the fertility rate so that the national rate matched the percent of female adults between 19 and 45 that report being currently pregnant in the 2016 National Health Interview Survey, and imputed pregnancy status based on this adjusted rate.<sup>8</sup>

Undocumented immigrants are not eligible for Medicaid or Federal insurance subsidies. Pew reports estimates on the percent of the foreign-born population in each state that is undocumented. Using these rates, we simulated documentation status for respondents who report being born outside of the United States. Respondents assumed to be undocumented were deemed ineligible for Medicaid and Federal insurance subsidies.

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<sup>6</sup> U.S. unauthorized immigrant population estimates by state, 2016. Pew Research Center.

<http://www.pewhispanic.org/interactives/u-s-unauthorized-immigrants-by-state/>

<sup>7</sup> Using SHADAC Health Insurance Unit (HIU) and Federal Poverty Guideline (FPG) Microdata Variables. State Health Access Data Assistance Center (SHADAC). <https://bit.ly/2tkYHAT>. We modified the SHADAC programs to allow for same-sex marriages and to combine college students with their parents.

<sup>8</sup> National Health Interview Survey. National Center for Health Statistics. Available at <https://www.cdc.gov/nchs/nhis/index.htm>.

Though all states use MAGI-based FPL ratios when assessing Medicaid eligibility, the FPL Ratio eligibility threshold is state-specific. States may set different eligibility thresholds for children, parents, pregnant women, and newly-eligible adults. To assess an individual's Medicaid eligibility, we compared their family's FPL ratio to the eligibility threshold for the state corresponding to that individual's eligibility pathway. Recipients of Supplemental Security Income (SSI) are also typically eligible for Medicaid through the elderly/disabled eligibility pathway. Thus, we also assumed those reporting SSI were Medicaid eligible.

We also assess eligibility for federal subsidies on the insurance marketplaces. To be eligible for the subsidies, one must have an FPL ratio between 100% and 400%, must not be eligible for Medicaid, must not have access to employer coverage, and must not be an undocumented immigrant. We assume those who are not enrolled in employer coverage do not have access to employer coverage. For those with FPL ratios between 100% and 400% of the FPL Marketplace subsidies are calculated using the following formula:

$$\text{Premium Subsidy} = \max[0, \text{Second Lowest Cost Silver Plan Premium} - \text{HIU MAGI} * \text{Premium Cap Percentage}]$$

The premium cap percentage is set by policy and varies by income from 2.08% to 9.86% in 2019.<sup>9</sup> As premiums are dynamically set within the model, the exact subsidy will vary under different policy scenarios. However, we treat the product of the HIU MAGI and the Premium Cap Percentage as exogenous and calculate this amount for each eligible family during this module.

## Module 3: Health Status

### Overview

We estimate rates of different health indicators by age, sex, race, education, and geography. We use these rates to impute health status for every respondent in our ACS data extract. Our methodology was implemented through the following four steps:

1. We estimate incident rates of different health indicators using regression analyses based on data in the Behavioral Risk Factor Surveillance System (BRFSS).
2. We assign health indicator probabilities to each adult respondent within our ACS Data Extract.
3. We adjust these probabilities to match state rates of health indicators measured in the BRFSS.
4. We use these adjusted probabilities to simulate health indicators for each ACS respondent.

### Data

#### Behavioral Risk Factor Surveillance System (BRFSS)

The BRFSS is a telephone survey administered by the Centers for Disease Control and Prevention (CDC). Each year, the survey collects health information from 400,000 U.S. adult respondents located in all 50

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<sup>9</sup> Explaining Health Care Reform: Questions About Health Insurance Subsidies. Kaiser Family Foundation. Available at <https://bit.ly/2IMFSkO>.

states and the District of Columbia. The survey collects information on demographics, health status, chronic conditions, and disability status.

### Approach

We use the BRFSS and regression analysis to predict ten separate health indicators:

1. *Health Status*. General health status (e.g. excellent, very good, good, fair, poor)
2. *Smoking*. Ever having smoked cigarettes
3. *Obesity*. Body mass index of 30 or above
4. *Diabetes*. Ever diagnosed with diabetes
5. *Asthma*. Ever diagnosed with asthma
6. *Skin Cancer*. Ever diagnosed with skin cancer
7. *Other Cancer*. Ever diagnosed with other cancer
8. *Heart Attack*. Ever diagnosed with heart attack
9. *Angina*. Ever diagnosed with angina
10. *Stroke*. Ever diagnosed with stroke

We used a multinomial logistic regression model for predicting general health status, and binary logistic regression models for the other outcomes. Each model controlled for respondent age, sex, race, education, disability status, and state of residence. The models were run in the sequence listed above. Each model controlled for health indicators that had already been predicted. For example, our diabetes model controlled for general health status, smoking and obesity. This approach allowed for correlation across different chronic conditions.

**Figure 3. BRFSS Health Indicator Regression Coefficients (\*p<0.05, \*\*p<0.01, \*\*\*p<0.001)**

	Excellent	Good	Fair	Poor	Smoking	Obesity	Diabetes	Asthma	Skin Cancer	Other Cancer	Heart Attack	Angina	Stroke
<b>Age Category</b>													
25-29 Years	-0.09*	0.21***	0.37***	0.72***	0.96***	0.56***	0.26	-0.20***	0.55*	0.70***	0.14	0.15	0.41
30-34 Years	-0.11**	0.30***	0.59***	0.95***	1.16***	0.71***	0.80***	-0.48***	0.81***	1.05***	0.32	0.52	0.77*
35-39 Years	-0.09*	0.34***	0.72***	1.11***	1.26***	0.86***	1.31***	-0.52***	1.40***	1.26***	0.64**	0.78*	0.91**
40-44 Years	-0.12**	0.44***	0.92***	1.41***	1.11***	0.92***	1.77***	-0.62***	1.93***	1.64***	1.34***	1.28***	1.43***
45-49 Years	-0.12**	0.45***	0.86***	1.52***	1.13***	0.95***	2.11***	-0.73***	2.21***	1.78***	1.41***	1.36***	1.53***
50-54 Years	-0.18***	0.42***	0.92***	1.69***	1.17***	0.84***	2.37***	-0.73***	2.75***	2.06***	1.85***	1.77***	1.58***
55-59 Years	-0.28***	0.44***	1.01***	1.85***	1.28***	0.74***	2.69***	-0.85***	3.06***	2.30***	2.03***	2.13***	1.83***
60-64 Years	-0.32***	0.50***	1.16***	1.98***	1.26***	0.72***	2.87***	-0.91***	3.33***	2.50***	2.27***	2.25***	1.89***
65-69 Years	-0.40***	0.45***	1.13***	1.93***	1.42***	0.72***	3.25***	-0.91***	3.63***	2.89***	2.62***	2.61***	2.15***
70-74 Years	-0.42***	0.44***	1.09***	1.92***	1.48***	0.55***	3.37***	-0.99***	3.95***	3.13***	2.77***	2.72***	2.34***
75-79 Years	-0.47***	0.56***	1.15***	1.97***	1.32***	0.28***	3.33***	-1.10***	4.18***	3.16***	2.89***	2.80***	2.41***
80+ Years	-0.45***	0.50***	1.01***	1.64***	0.90***	-0.39***	3.14***	-1.31***	4.36***	3.29***	3.11***	2.98***	2.57***
<b>Race/Ethnicity</b>													
Black	0.15***	0.49***	0.58***	0.29***	-0.63***	0.31***	0.42***	0.09**	-2.73***	-0.19***	-0.16**	-0.33***	0.26***
AIAN	0.09	0.39***	0.63***	0.78***	0.12*	0.23***	0.45***	0.17*	-0.64***	0.11	0.24*	-0.12	0.15
Asian	0.08	0.49***	0.38***	0.41*	-1.03***	-1.12***	0.68***	-0.50***	-3.37***	-0.35*	-0.26	-0.11	-0.55*
Hispanic	0.21***	0.67***	1.23***	1.00***	-0.89***	0.07*	0.28***	-0.35***	-1.66***	-0.60***	-0.32***	-0.28**	-0.32***
Female	-0.08***	-0.04*	-0.06*	-0.22***	-0.57***	-0.06***	-0.25***	0.36***	-0.15***	0.42***	-0.80***	-0.33***	-0.04
<b>Education</b>													
Some College	-0.05	-0.37***	-0.66***	-0.85***	-0.18***	0.05*	0.03	0.14***	0.24***	0.20***	0.00	0.19***	0.04
Bachelors	0.18***	-0.72***	-1.30***	-1.48***	-0.86***	-0.29***	-0.12***	0.20***	0.49***	0.33***	-0.23***	0.28***	-0.19***
<b>Disability</b>													
Hearing	-0.19***	0.18***	0.33***	0.40***	0.17***	-0.06*	0.04	0.21***	0.24***	0.11**	0.09*	0.18***	0.09
Vision	-0.08	0.20***	0.60***	0.79***	0.13***	-0.11**	0.31***	0.17***	0.11*	-0.02	0.26***	0.10	0.37***
Cognitive	-0.47***	0.48***	1.17***	1.62***	0.47***	-0.09***	0.04	0.38***	0.11**	0.21***	0.16***	0.16**	0.50***
Walking	-0.59***	0.81***	1.81***	2.61***	0.15***	0.66***	0.29***	0.40***	0.06	-0.06	0.35***	0.29***	0.44***
Self-Care	0.07	0.28***	0.58***	1.17***	0.02	0.09*	-0.12*	0.08	0.04	-0.08	-0.15*	0.05	0.12
Independence	-0.11	0.49***	0.97***	1.58***	0.15***	-0.16***	0.00	0.15***	-0.05	0.06	0.10	0.07	0.40***
<b>Health Status</b>													
Very Good					0.25***	0.69***	0.81***	0.32***	0.08*	0.43***	0.45***	0.49***	0.59***
Good					0.42***	1.20***	1.56***	0.48***	0.10**	0.82***	1.03***	1.09***	1.02***
Fair					0.55***	1.35***	2.10***	0.77***	0.15**	1.18***	1.56***	1.53***	1.39***
Poor					0.62***	1.18***	2.40***	1.00***	0.29***	1.55***	2.01***	1.87***	1.58***
Smoking						-0.18***	-0.07**	0.13***	0.03	0.18***	0.46***	0.19***	0.17***
<b>Chronic Conditions</b>													
Obesity							0.91***	0.29***	-0.18***	-0.04	0.07*	0.18***	-0.16***
Diabetes								0.14***	-0.07*	-0.04	0.48***	0.42***	0.27***
Asthma									0.27***	0.15***	0.23***	0.25***	0.23***
Skin Cancer										0.65***	0.10*	0.22***	0.06
Other Cancer											0.05	0.12**	0.02
Heart Attack												2.66***	1.06***
Angina													0.23***
Constant	-0.50***	-0.27***	-1.89***	-4.23***	-1.02***	-2.15***	-6.05***	-2.31***	-5.19***	-6.05***	-5.99***	-6.68***	-6.50***

Our health indicator models were designed so that they could be used to make predictions within our ACS Data Extract. Despite controlling for state fixed effects, these predicted probabilities would not necessarily produce the same state-specific health indicator rates that are observed in the BRFSS. This is partially due to differences in the measured covariates between the two surveys. For example, measured rates of ambulatory and cognitive disabilities are lower in the BRFSS than the ACS. Thus, we adjust the health indicator rates that we predict in the ACS to be consistent with the BRFSS state rates. Finally, we simulate health indicators within the ACS data extract. We complete these describe steps in sequence for each health indicator, before proceeding to the next health indicator. As such, we can account for the previously simulated health indicators, when simulating subsequent health indicators. For example, when we simulate whether a respondent has diabetes, the probability we assign is influenced by whether that respondent's simulated health status, smoking status, and obesity status.

We do not simulate health indicators for ACS respondents under the age of 18.

## Module 4: Utilization

### Overview

We estimate utilization by age, sex, race, family structure, health status, payer, geography, and service category. We impute utilization rates for every respondent in our ACS data extract, and then scale these rates to regional benchmarks. Our methodology was carried out in six steps:

1. We use the Medical Expenditure Panel Survey (MEPS) to model utilization rates among the commercially-insured population for the following health care services:
  - Hospitalizations
  - Outpatient visits
  - Emergency room (ER) visits
  - Physician visits
  - Prescription drug fills and refills
2. We use findings from the Oregon Health Insurance Experiment to reduce utilization rates for people without health insurance coverage.
3. We use these models and adjustments to assign utilization rates to each respondent in our ACS Data Extract.
4. We develop state-level utilization benchmarks for the commercially-insured population, and scale utilization rates so they are consistent with those benchmarks.
5. We perform a final scaling adjustment to our utilization rates so that they align with national utilization rates by age and sex published by the Health Care Cost Institute (HCCI).
6. We developed a methodology to increase intrapersonal correlation across service categories to empirically observed levels.

## Data

### Medical Expenditure Panel Survey (MEPS)

The Medical Expenditure Panel Survey (MEPS) includes a large household survey that tracks individual characteristics, health status, and health care utilization. We used the 2014-2016 MEPS to develop regression models to predict health care utilization.

### Annual Health Care Cost and Utilization Report (HCCUR)

The Annual Health Care Cost and Utilization Report (HCCUR) from the HCCI provides estimates for national utilization rates a commercially insured population. The data set is based on claims data from four major commercial insurers (Aetna, Humana, Kaiser Permanente, and United HealthCare), covers all 50 states, and represents “health care activity of about 26% of all individuals younger than 65 [on employer sponsored insurance].” For each service category, the file provides utilization, spending, and price estimates by age category, sex, and year.

We rely on the 2016 HCCUR file for national utilization levels for those covered by commercial insurance.

### Healthcare Cost Report Information System (HCRIS)

All hospitals receiving Medicare payments are required to submit a Medicare Cost report to the Centers for Medicare & Medicaid Services (CMS) through the Healthcare Cost Report Information System (HCRIS).<sup>10</sup>

We rely on the 2015-2017 hospital HCRIS files for the total number of hospitalizations occurring within each state.

### Nationwide Inpatient Sample (NIS)

The Nationwide Inpatient Sample (NIS) is a 20% sample of hospital discharges in the United States administered by the Agency for Healthcare Research and Quality. The 2015 dataset can be queried online using HCUPnet. The dataset includes data from 36 states.

We rely on the NIS for the number of privately-insured discharges for the 36 included states.

### Area Health Resource File (AHRF)

The Area Health Resource File (AHRF) contains state- and county-level data on a variety of health metrics, including workforce capacity, population characteristics, and utilization. The AHRF is assembled by the Health Resources and Services Administration (HRSA).

We rely on the AHRF for total (i.e. all-payer) state-level counts of outpatient visits in 2014. This information is originally sourced from the American Hospital Associations Annual Survey Database.

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<sup>10</sup> Cost reports. Centers for Medicare & Medicaid Services. Available at <https://go.cms.gov/2qQwlzC>.

### HCCI ER Spending, Use, and Price Trends

HCCI has released an Excel report on state-level variation in ER spending, utilization and price between 2009 and 2016. ER visits are defined by current procedure terminology (CPT) codes 99281-99285.

We used the 2016 version of the file to estimate state-level variation in ER visits.

### HCCI Trends in Primary Care Visits

In November 2018, the HCCI released a dataset showing state-level trends in office visits between 2012 and 2016.<sup>11</sup> Office visits were defined by CPT codes 99201-99215 and 99341-99350. Visits were classified into five categories:

- Primary care physicians
- MD specialist
- Nurse practitioners
- Physician assistants
- All other non-MD providers

We used the 2016 version of this file to estimate state-level variation in physician visits.

### Modeled Utilization in the MEPS

We used the 2014-2016 MEPS to model the following categories of utilization:

- Hospitalizations
- Outpatient hospital visits
- Emergency room visits
- Physician visits
- Prescription drug fills and refills

For each service category, we assumed utilization counts followed a zero-inflated Poisson (ZIP) distribution. ZIP distributions are useful for representing count variables when there are a disproportionately high number of zero values. We estimated these parameters using regression models for each service category. Our regression sample was limited to MEPS respondents who were (1) under age 65, (2) had consistent coverage throughout the year, (3) were enrolled in private insurance coverage (employer or non-group), and (4) had non-missing responses for all variables used as outcomes or covariates. We accounted for the complex multistage sampling design of the MEPS using person-level weight, variance for primary survey unit and variance for strata.

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<sup>11</sup> Trends In Primary Care Visits. Health Care Cost Institute. Available at <https://bit.ly/2zSNryw>.

We ran separate models for non-elderly adults (aged 18-64) and children (aged 0-17). Each non-elderly adult model included the survey year and the following covariates:

<i>Demographics</i>	Sex, age, race, and geographic region
<i>Family Structure</i>	Family size and marital status
<i>General health status</i>	Reported general health as excellent, very good, good, fair, or poor
<i>Disability</i>	Difficulty with vision, hearing, ambulation, cognitive, self-care, and/or independent living
<i>Healthy Behaviors</i>	Smoking status
<i>Chronic conditions</i>	A medical diagnosis of obesity, diabetes, asthma, heart attack, angina, stroke, skin cancer, other cancer

As children in the sample generally had very low utilization in many of the service categories, we found a simpler model provided a better fit for the data. Thus, for children, we only controlled for age.

#### Adjusting Utilization for Uninsured Populations

As insurance coverage reduces the marginal cost of health care for individuals, gaining or losing health insurance likely has a causal effect on utilization rates. The Oregon Health Insurance Experiment (OHIE) estimated these effects in a randomized controlled experiment, and found that gaining Medicaid resulted in the following effects<sup>12</sup>:

- **Hospitalizations** increased by 30%
- **ER visits** increased by 68%
- **Physician office visits** increased by 50%
- **Prescription drugs** used increased by 15%

Our MEPS-based utilization models could be used to predict rates for an individual under a scenario when that individual was commercially-insured. We used the above findings from the OHIE to adjust utilization rates to represent a scenario when that same individual was uninsured. For example, if our MEPS model predicted that an individual had a 10.0% chance of being hospitalized, and a conditional mean number of hospitalizations of 1.20, we assumed that if that same person was uninsured, they would have an 8.8% ( $0.10/\sqrt{1.3}$ ) chance of being hospitalized and a conditional mean number of hospitalizations of 1.05 ( $1.25/\sqrt{1.3}$ ).

OHIE did not report an impact on utilization for hospital outpatient visits. We averaged the four reported effects and assumed that insured persons use 41% more hospital outpatient visits.

<sup>12</sup> Katherine Baicker, Sarah Taubman, Heidi Allen, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Eric Schneider, Bill Wright, Alan Zaslavsky, Amy Finkelstein, and the Oregon Health Study Group, "The Oregon Experiment – Effects of Medicaid on Clinical Outcomes", *New England Journal of Medicine*, 2013 May; 368(18): 1713-1722.

### Assigning Utilization Rates to ACS Respondents

We intentionally restricted the covariates in the MEPS utilization models to only include variables that were directly included in the ACS or could readily be imputed in the ACS using our BFRSS chronic condition models. Thus, we could use the MEPS models to predict utilization rates for each respondent in our ACS Data Extract.

If an outcome (Y) for an individual (i) follows a ZIP distribution, then distribution of Y can be expressed as

$Y_i = 0$  with probability  $P_i$

$Y_i \sim \text{Poisson}(\mu_i)$  with probability  $1 - P_i$

To simulate from this distribution, we require  $P_i$  (the probability of having any utilization) and  $\mu_i$  (the conditional mean utilization). Both parameters can be obtained using our MEPS-based regression models. Then, we simulated utilization for person i and service category j through the following procedure:

- (1) Simulate  $X_{ij}$  from Uniform(0,1)
- (2) If  $X_{ij} < P_{ij}$  then set  $Y_{ij}$  equal to 0. Otherwise, simulate  $Y_{ij}$  from Poisson( $\mu_{ij}$ )

### Scaling to State-Level Utilization Benchmarks

Our MEPS-based utilization models included four-level geographic region code. Yet, there is significant variation in utilization across states, even within a geographic region. To account for this, we created state-level utilization indices for the utilization of inpatient services, outpatient hospital services, ER services, and physician services. These indices were applied to national utilization rates by age and gender from HCCI, to develop state-level utilization benchmarks. Our MEPS-based utilization rates were adjusted to make them consistent with these benchmarks. We did not scale pharmacy utilization to an external benchmark.

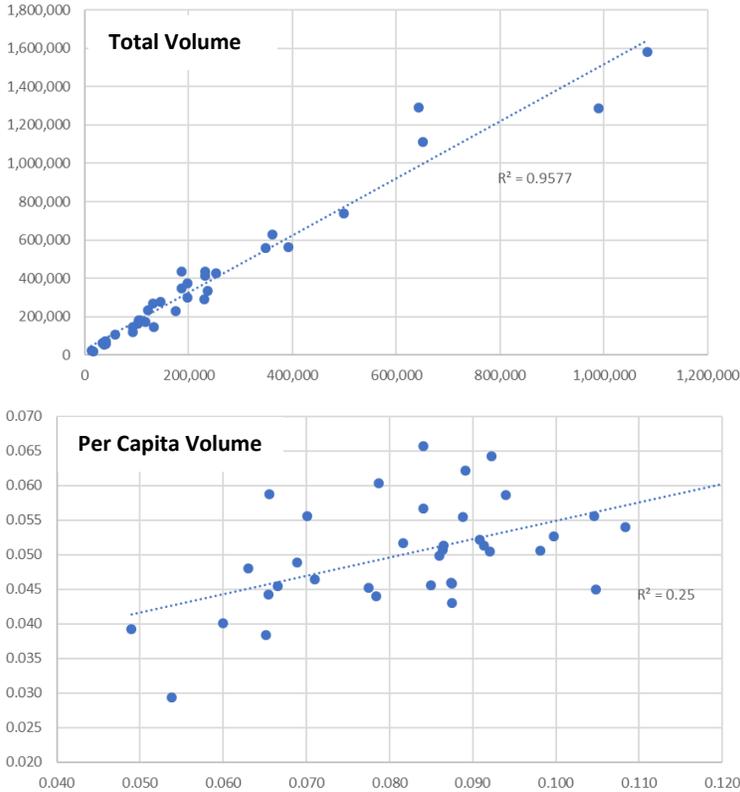
### Constructing an Inpatient and Outpatient Utilization Index

For inpatient and outpatient services, we estimated commercial volume in each state using a two-part process:

- (1) Estimate total volume across all payers
- (2) Estimate the commercially-insured's share of volume
- (3) Multiply #1 and #2 to estimate commercially-insured volume

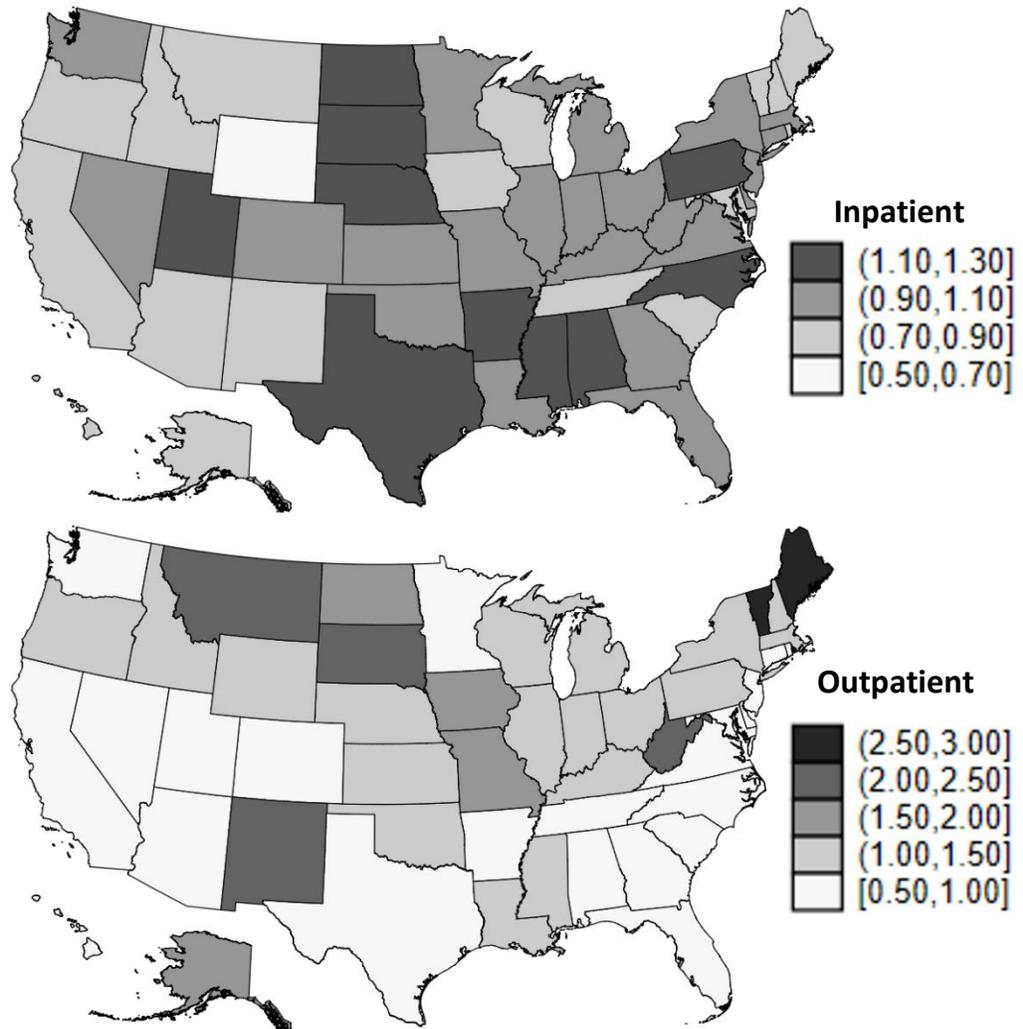
For inpatient hospital services, total volume by state was estimated using HCRIS (Worksheet S3, Part 1, Line 14, Column 15). For outpatient hospital services, total volume by state was estimated using the AHRF. For both inpatient and outpatient services, we estimated the commercially-insured's share of volume by applying MEPS-based age-sex-payer utilization rates to state-level population estimates from the ACS. We could directly observe inpatient volume for the privately insured in the NIS for 36 states. Thus, we only used our ACS-MEPS-based inpatient volume measure for states that were not included in the NIS. We found that our ACS-MEPS-based inpatient measure correlated reasonably well with actual estimates from NIS (see Figure 4).

Figure 4. Correlation between HCRIS-MEPS-ACS Inpatient Volume Estimates and NIS Estimates



We combined our state-level service volume estimates with state-level commercially-insured population estimates to calculate utilization rates. The state utilization rate was divided by a national utilization rate to construct a state-level utilization index. Figures 5 shows the state-level indices for inpatient and outpatient hospital services.

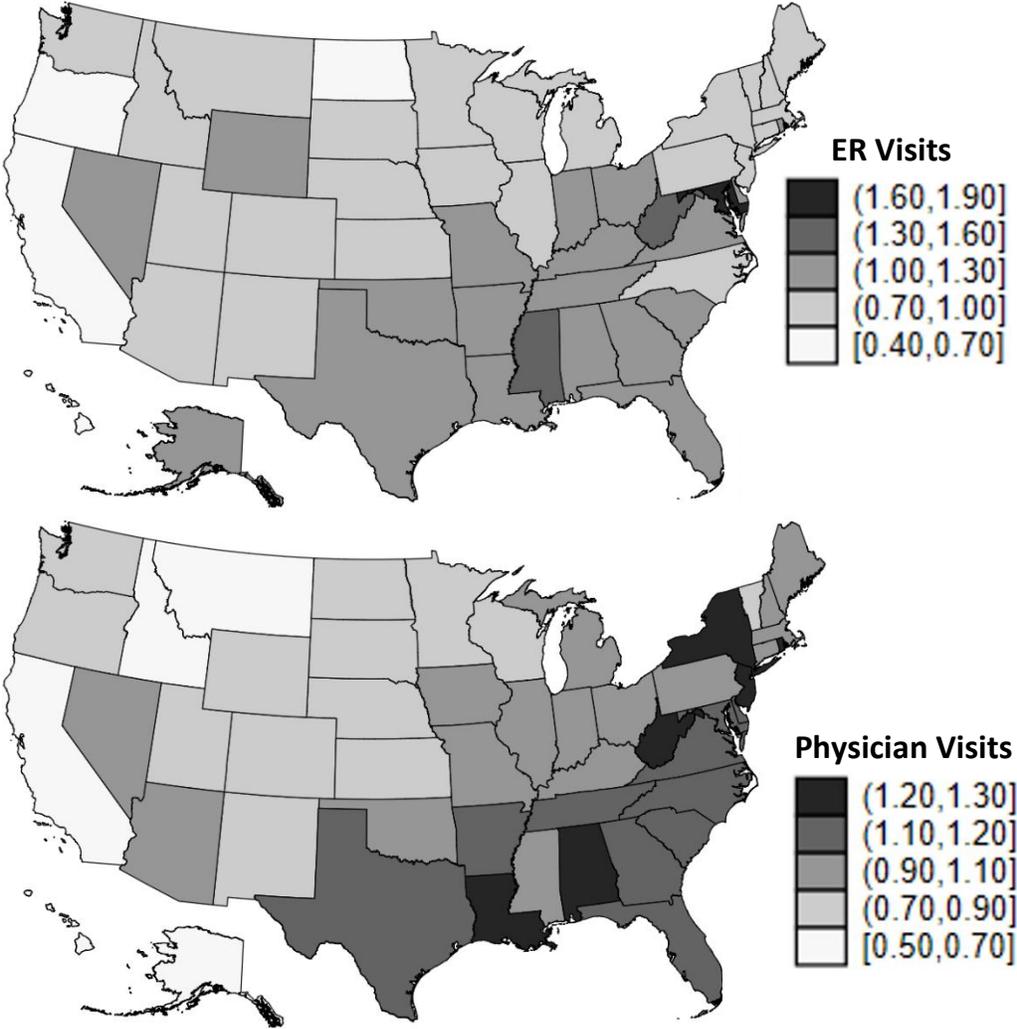
**Figure 5. Inpatient and Outpatient Utilization Indices**



Constructing an ER and Physician Utilization Index

HCCI has released special reports that report commercial ER and physician utilization rates by states. We used these data sources to construct utilization indices for ER visits and physician visits, which are shown in Figure 6.

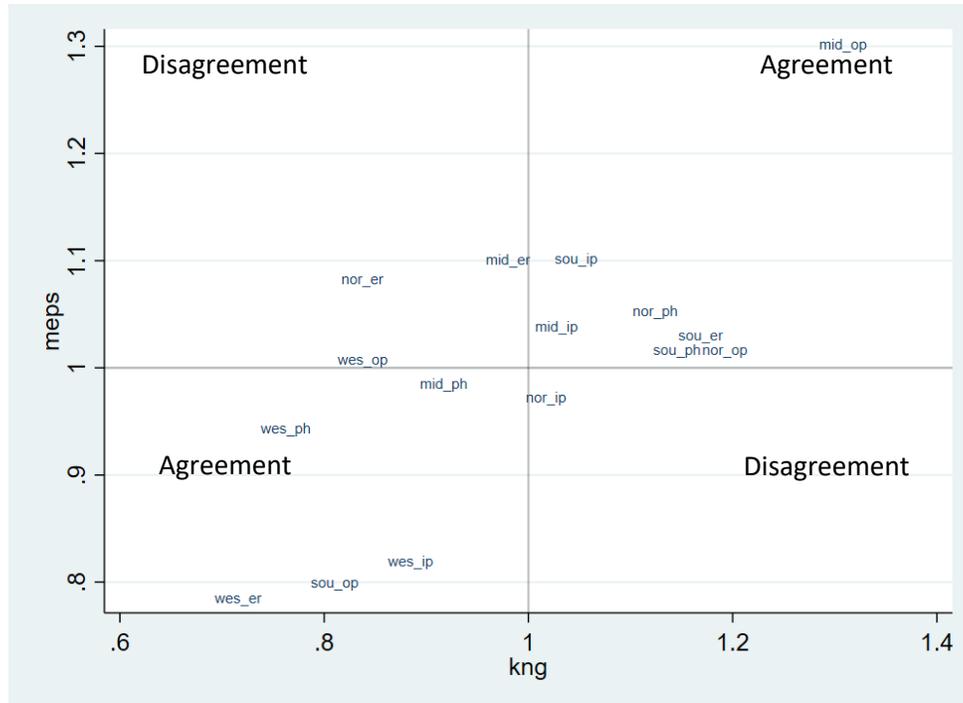
Figure 6. ER and Physician Utilization Indices



Examining Utilization Indices

We compared our utilization indices to geographic variation reported in the MEPS. To do this, we constructed a 4-code Census Region-level index for each service category using both our indices and the MEPS. As shown in Figure 7, our utilization indices agreed with the MEPS for 12 of 16 service-region combinations. The most significant discordance related to northeastern ER utilization – where we find below-average utilization while MEPS finds above-average utilization.

**Figure 7. MEPS Utilization Indices (meps) vs. KNG Health Utilization Indices (kng)**  
*physician (ph), emergency room (er), inpatient (ip), and outpatient (op)*  
*northeast (nor), south (sou), midwest (mid), west (wes)*



### Scaling to Utilization Benchmarks

We extracted national utilization rates from HCCI. These national utilization rates were multiplied by our utilization indices to estimate a state-level utilization benchmark. Individual utilization rates were adjusted to be consistent with these benchmarks. As a final step, we scaled utilization rates in each service category to match HCCI utilization levels by age and sex.

## Module 5: Prices

### Overview

To convert utilization into spending levels, we estimated unit prices by service category, age, sex, payer, and geographic region. We rely on national price levels from the HCCI, and then adjust for differences across payers and regions. We developed our estimates by implementing the following four steps:

1. We extracted national commercial prices by age, sex, and service category from the HCCUR file.
2. We adjusted for differences in price levels across payers based on assumptions from the literature.
3. We adjust for geographic variation in commercial prices using the HCCI Healthy Market Index.
4. We adjust for geographic variation in Medicare prices using CMS payment system parameters.

## Data

### Healthy Market Index (HMI)

The Healthy Market Index (HMI) was developed by the HCCI to show geographic variation in health care prices within commercial insurance markets.<sup>13</sup> The HMI is designed to compare “the prices paid for the same set of services for largely similar populations across areas.”<sup>14</sup> The HMI is provided for metropolitan statistical areas (MSAs), which are geographic areas defined by urban centers of at least 100,000 people. While there are 378 MSAs, HCCI only releases information for 111 MSAs. Separate HMIs are provided for inpatient, outpatient, and physician services. The outpatient HMI includes emergency room services.

### Inpatient Prospective Payment System (IPPS) Impact File

The Inpatient Prospective Payment System (IPPS) Impact File provides data that are used to determine hospital-specific inpatient Medicare payment rates.<sup>15</sup>

### Outpatient Prospective Payment System (OPPS) Impact File

The Outpatient Prospective Payment System (OPPS) Impact File provides data that are used to determine hospital-specific outpatient Medicare payment rates.<sup>16</sup>

### Medicare Physician Fee Schedule (MPFS) Addendum

The Medicare Physician Fee Schedule Addendum files provide data that are used to determine locality-level physician Medicare payment rates.<sup>17</sup>

## Approach

### National Price Levels by Payer

We extracted national 2016 price levels for each service category from the HCCUR. These reflect prices paid on behalf of those with commercial coverage. To adjust for differences across payers, we reviewed studies that compared Medicare and commercial prices for the same set of services. In 2017 and 2018, the Congressional Budget Office (CBO) released two studies comparing prices for commercial and Medicare hospital admissions and physician care. In their analysis of hospitals using data from the Health Care Cost Institute (HCCI), CBO found that commercial insurers paid 89% more than Medicare for inpatient hospitalizations.<sup>18</sup> The findings were similar for both medical and surgical admissions.

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<sup>13</sup> Healthy Marketplace Index. Health Care Cost Institute. Available at <https://www.healthcostinstitute.org/research/hmi>.

<sup>14</sup> 2018 Healthy Market Place Index Frequently Asked Questions. Health Care Cost Institute. Available at <https://bit.ly/2BMdKav>.

<sup>15</sup> FY 2016 Final Rule and Correction Notice Data Files. Centers for Medicare & Medicaid Services. Available at <https://go.cms.gov/2s0L2hQ>.

<sup>16</sup> FY 2016 Final Rule. Centers for Medicare & Medicaid Services. Available at <https://go.cms.gov/2U49g74>.

<sup>17</sup> CY 2016 Final Rule. Centers for Medicare & Medicaid Services. Available at <https://go.cms.gov/2TgeYFP>.

<sup>18</sup> An Analysis of Private-Sector Prices for Hospital Admissions. Congressional Budget Office. 2017. Available at <https://www.cbo.gov/system/files/115th-congress-2017-2018/workingpaper/52567-hospitalprices.pdf>.

CBO also found that commercial insurers paid more than Medicare for physician services but did not report an overall average difference.<sup>19</sup> We used the service taxonomy provided by the HCCI to classify the twenty physician services analyzed by CBO into four physician service categories: office visits, surgical services, radiology services, and other professional services.<sup>20</sup> Within a service category, we computed an unweighted average commercial-to-Medicare payment ratio for all reported services in the category. Next, we linked these average ratios to commercial per-capita spending amounts from the HCCI. We then computed an overall mean commercial-to-Medicare payment ratio by computing the average commercial-to-Medicare payment ratios across the four service categories, weighted by the per-capita spending amount in each service category. This calculation resulted in an overall commercial-to-Medicare ratio of 1.49 for physician services.

**Figure 8. Calculation of Overall Physician Commercial-to-Medicare Payment Ratio**

Service Category	Commercial Per Capita Spending	Mean Commercial-to-Medicare Payment Ratio
Office Visits	\$385.91	1.12
Surgical Services	\$280.63	1.70
Radiology Services	\$133.58	2.17
Other Professional Services	\$523.26	1.47
Weighted Mean Commercial-to-Medicare Ratio		1.49

**Sources:** Maeda 2017; Health Care Cost Institute Annual Report

**Categories:** Office Visits: 99203, 99213, 99214; Surgical services: 17311, 19081, 27130, 27447, 29881, 45385, 47562, 58558, 66984; Radiology services: 70553, 74183, 77418, 78815; Other Professional: 92928, 93000, 93458, 99232

CBO has not released an analysis comparing differences in commercial and Medicare payment rates for outpatient hospital services. In a 2017 Report to Congress, the Medicare Payment Advisory Commission (MedPAC) stated that commercial rates “are often far more than 50 percent above Medicare rates.”<sup>21</sup> A 2010 study from the Center for Studying Health System Change found that private insurer rates for hospital outpatient services were between 134% and 266% of Medicare rates across eight studied markets.<sup>22</sup> This is consistent with public filing reports from California insurers which showed commercial outpatient rates that were 200% more than Medicare.<sup>21</sup> The American Hospital Association reports

<sup>19</sup> An Analysis of Private-Sector Prices for Physicians’ Services: Working Paper 2018-01. Congressional Budget Office. 2018. Available at <https://www.cbo.gov/publication/53441>.

<sup>20</sup> HCCI Professional Service Categories – CPT Procedure Codes. Health Care Cost Institute. 2016. Available at <https://www.healthcostinstitute.org/research/research-resources>.

<sup>21</sup> Report to the Congress: Medicare Payment Policy Chapter 3. Medicare Payment Advisory Commission. 2017. Available at [http://www.medpac.gov/docs/default-source/reports/mar17\\_medpac\\_ch3.pdf?sfvrsn=0](http://www.medpac.gov/docs/default-source/reports/mar17_medpac_ch3.pdf?sfvrsn=0)

<sup>22</sup> Wide Variation in Hospital and Physician Payment Rates Evidence of Provider Market Power. Center for Studying Health System Change. 2010. Available at <http://www.hschange.org/CONTENT/1162/>.

aggregate hospital payment-to-cost ratios by payer, which reflect both inpatient and outpatient services.<sup>23</sup> In 2016, the commercial payment-to-cost ratio was 67% higher than the Medicare payment-to-cost ratio. Based on this research and discussions with hospital industry experts, we assume a commercial-to-Medicare ratio of 2.25 for outpatient hospital services.

There is limited research on prices paid for uninsured patients. A Health Affairs study found that uninsured patients paid similar prices to Medicare patients for hospital services.<sup>24</sup> Another study published in the Journal of Health Economics found that prices paid for the uninsured were comparable, or even higher, than prices paid for insured patients.<sup>25</sup> Our own analysis of financial data from the AHA Annual Survey showed similar hospital payment-to-cost ratios for uninsured and Medicare patients. Based on this analysis and the studies we reviewed, we assumed the uninsured paid Medicare prices for hospital care and commercial prices for physician care. Figure 9 shows the prices we used by payer.

### Regional Commercial Prices

The HMI reports the ratio of price levels in a subset of core-based statistical areas (CBSAs) relative to the national average. Separate indices are reported for different service categories. We can estimate market-specific commercial prices by multiplying national price levels by the HMI ratio for the corresponding service category. An HMI is only reported for 112 CBSAs. For both the remaining 812 CBSAs and rural areas, we assign the HMI value for the nearest CBSA with a reported value (see Figure 10). If the nearest CBSA is more than 100 miles away, we assign the average HMI for the geographic region.

### Regional Medicare Prices

To estimate regional Medicare prices, we estimated service-specific Medicare price indices based on the payment parameters used by CMS when determining reimbursement. For inpatient services, the regional index value was based on the CMS wage index adjustment, cost-of-living adjustment, disproportionate share hospital adjustment, and teaching hospital adjustment. For outpatient services, the regional index value was based on the CMS wage index adjustment and an adjustment for sole community hospitals. For physician services, the regional index value was based on the MPFS geographic practice cost index parameters.

### Prescription Drug Prices

For prescription drugs we rely on a KFF report based on data request from IQVIA. This report shows the national total number of retail prescription drugs filled at pharmacies, and associated spending.<sup>26</sup> We used these data to estimate a national price per filled prescription of \$95.23. We did not vary this price by payer, geography, or patient type.

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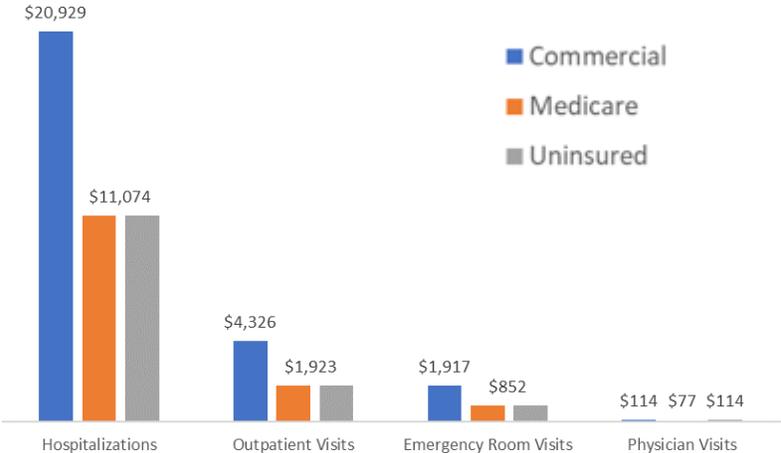
<sup>23</sup> Trendwatch Chartbook 2018 Chart 4.6. American Hospital Association. 2018. Available at <https://www.aha.org/system/files/2018-05/2018-chartbook-chart-4-6.pdf>.

<sup>24</sup> Hospital Pricing And The Uninsured: Do The Uninsured Pay Higher Prices? Melnick GA, Fonkych K. Health Affairs. April 2008. <https://www.healthaffairs.org/doi/full/10.1377/hlthaff.27.2.w116>.

<sup>25</sup> How much uncompensated care do doctors provide? Gruber J, Roriguez R. Journal of Health Economics. September 2007. <https://economics.mit.edu/files/6423>.

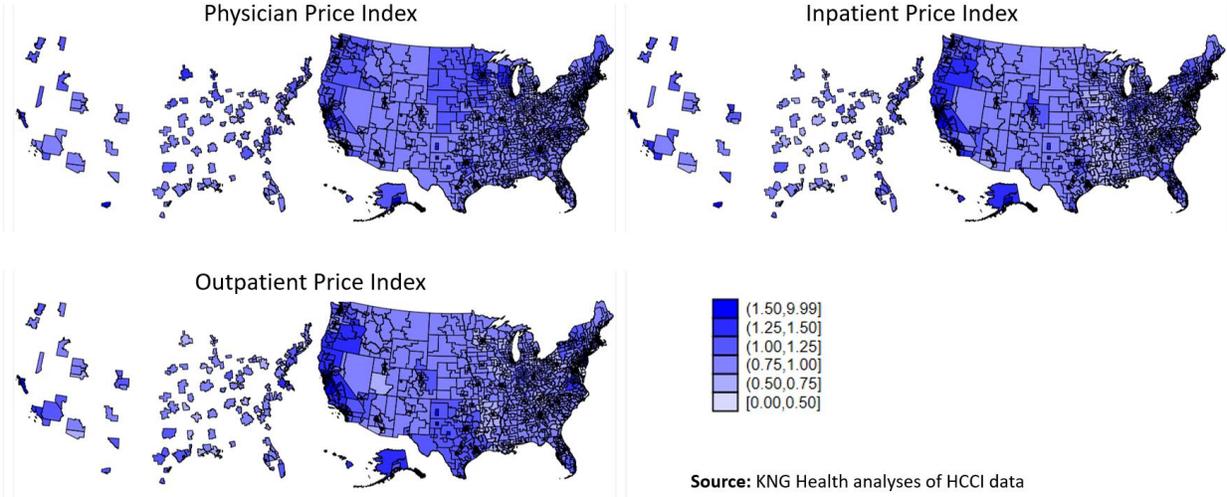
<sup>26</sup> Health Costs & Budgets Indicators – Prescription Drugs. Kaiser Family Foundation. Available at <https://bit.ly/2Hpo2lm>.

**Figure 9. Assumed national average prices by payer**



Source: KNG Health analysis of 2016 HCCI Annual Report file

**Figure 10. Imputing missing HMI values across all regions**



## Module 6: Out of Pocket Costs

### Overview

We calculate out-of-pocket costs (OOP) using a simplified benefit design model with four payer-specific parameters: a deductible, a pre-deductible co-insurance rate, a post-deductible co-insurance rate, and an OOP maximum. Our methodology for establishing and applying these parameters was carried out in the following three steps:

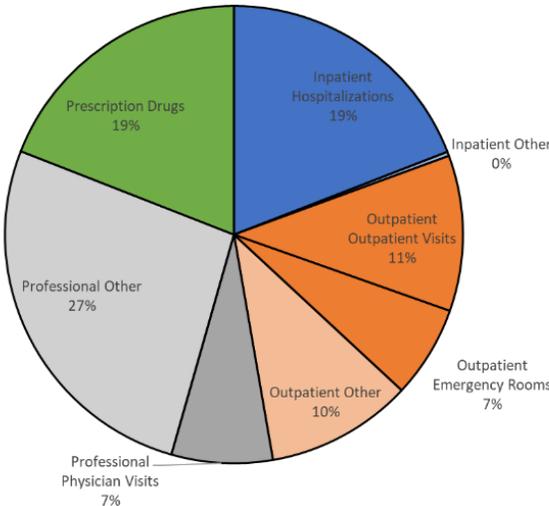
1. We calculated health spending by multiplying simulated utilization counts by corresponding unit prices and adjusted for categories of spending not encompassed by our service categories.
2. We identified national average deductibles, out-of-pocket maximums, and actuarial value for different types of coverage.
3. We parameterize pre-deductible and post-deductible coinsurance rates, such that plan liability relative to spending is consistent with the plan’s assumed actuarial value.

### Approach

#### Estimating Individual Health Spending

Our utilization models allow us to simulate an individual’s annual number of hospitalizations, outpatient visits, emergency room visits, physician visits, and prescription drug utilization. In addition, the prices contained within our model allow us to convert utilization to health spending by service category. Not all spending can be attributed to those service categories. According to the HCCI, these service categories represent approximately 63% of all spending. More than 99% of other health spending is for either outpatient hospital services (e.g. ancillary, laboratory, and radiology) or professional services (e.g. anesthesia, surgery, drug administration).

**Figure 11. Average spending distributions for an individual with commercial insurance**



Source: KNG Health analysis of 2016 HCCI Annual Report file

To compute total health spending, we used the following formula:

$$\begin{aligned}
 \text{Spending} = & \text{Other spending adjustment} * \\
 & ( \text{Hospitalizations} \quad * \text{Hospitalization Price} \quad + \\
 & \quad \text{Outpatient Visits} \quad * \text{Outpatient Visit Price} \quad + \\
 & \quad \text{ER Visit} \quad * \text{ER Visit Price} \quad + \\
 & \quad \text{Physician Visit} \quad * \text{Physician Visit Price} \quad + \\
 & \quad \text{Prescription Drug Filling} \quad * \text{Prescription Drug Filling Price} \quad )
 \end{aligned}$$

On average, the other spending adjustment was the reciprocal of 63%, but we allowed this adjustment to vary by age and sex.

Estimating OOP Spending

Figure 12 shows our assumed 2018 deductibles and OOP maximums for both the employer and non-group market. These values were based on national average estimates reported by the Kaiser Family Foundation and HealthPocket.com.<sup>27,28</sup> We scaled these values to the particular year being modeled by adjusting for projected growth in the Medical Component of the Consumer Price Index (CPI-M).<sup>29</sup> We assumed these parameters applied to all individuals enrolled in that coverage type.

**Figure 12. Assumed 2018 Individual/Family Deductibles and OOP Maximums**

Cost-Sharing Parameter	ESI	Marketplace
Individual Deductible	\$1,562	\$4,033
Individual OOP Maximum	\$3,967	\$6,863
Family Deductible	\$3,419	\$7,474
Family OOP Maximum	\$6,875	\$12,952

Source: KNG Health analysis of data from Kaiser Family Foundation and HealthPocket

According to the Kaiser Family Foundation, most Marketplace enrollees choose a Silver Plan.<sup>30</sup> Silver Plans are defined as having an actuarial value of 70%. According to the Commonwealth Fund, a typical employer plan has an actuarial value comparable to a gold plan.<sup>31</sup> Thus, we assumed that employer plans would have an actuarial value of 80%.

We estimated OOP at the family-level by applying a coinsurance rate to the health spending level. The coinsurance rate varied depending on whether the family had met their deductible. We assumed ESI enrollees would pay a pre-deductible coinsurance rate of 30% and a post-deductible coinsurance rate of 6%. We assumed non-group market enrollees would pay a pre-deductible coinsurance rate of 40% and a

<sup>27</sup> 2017 Employer Health Benefits Survey. Kaiser Family Foundation. September 2017. Available at <https://www.kff.org/report-section/ehbs-2017-section-7-employee-cost-sharing/>

<sup>28</sup> Average Market Premiums Spike Across Obamacare Plans in 2018. HealthPocket. October 2017. Available at <https://bit.ly/2XKY6pU>

<sup>29</sup> The Budget and Economic Outlook: 2018 to 2028. Congressional Budget Office. August 2018. <https://www.cbo.gov/publication/54318>.

<sup>30</sup> Marketplace Enrollment by Metal Level. Kaiser Family Foundation. March 2016. Available at <https://www.kff.org/health-reform/state-indicator/marketplace-enrollment-by-metal-level/>.

<sup>31</sup> Consumer Cost-Sharing in Marketplace vs. Employer Health Insurance Plans. December 2015. Available at <https://bit.ly/2VGtRio>.

post-deductible coinsurance rate of 7%. These rates were selected because they resulted in reasonable actuarial value estimates. We did not allow OOP to exceed the maximum OOP limit for the plan.

## Module 7: Premiums

### Overview

We estimate non-group health insurance premiums endogenously based on estimates of plan liability within a risk pool and Marketplace premium setting rules. Our methodology for establishing premiums was carried out in the following five steps:

1. Define state-specific risk pools that consist of all individuals within the state enrolling in non-group coverage.
2. Calculate adjusted plan liability as the difference between simulated health spending and simulated OOP for all members within the risk pool, adjusted for the insurer's administrative costs.
3. Determine an enrollee-specific rating factor based on the enrollee's age, tobacco status, and family structure.
4. Within each risk pool, divide the total plan liability by the total rating factors, to determine a premium amount per rating weight.
5. Set employer plan premiums based on state average premiums reported in the MEPS.

### Approach

Using the methodology described in Module 6, we can simulate health spending and OOP for individuals electing to enroll in non-group coverage. The difference between health spending and OOP represents the portion of an enrollee's health costs paid by the insurer (i.e. the insurance plan liability). Premiums are established within a rating area such that they cover the plan's expected plan liability, plus administrative costs. We treat each state as a separate rating area.

We assume an administrative burden of 12%, based on private health insurance expenditure estimates reported in the National Health Expenditure Accounts.<sup>32</sup> For example, if we estimate \$88 million in plan liability within a rating area, we assume the insurer will need to collect \$100 million in premiums to cover both medical losses and overhead costs.

The ACA's market rating reforms limit the extent to which insurers can charge different prices based on health status. CMS publishes state-specific age curves which specify allowable age-specific variation in premiums.<sup>33</sup> Premiums can also be up-to 50% higher for tobacco users, though the exact rating difference varies by state. Lastly, no more than the three oldest covered children are considered when setting premiums. Using these rules, we assign a rating factor to each individual enrolling in non-group coverage. The premium per rating factor is computed as the total premiums in the rating area divided by the total rating factor. This ratio is used to price premiums, both for those who are enrolled or considering enrolling in non-group coverage.

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<sup>32</sup> National Health Expenditures by Source of Funds and Type of Expenditure: Calendar Years 2011-2017. Centers for Medicare & Medicaid Services. Available at <https://go.cms.gov/1Jy5kin>.

<sup>33</sup> Market Rating Reforms. Centers for Medicare & Medicaid Services. <https://go.cms.gov/2EGTRDd>.

We do not endogenously establish premiums for those enrolling in employer coverage. Instead, we rely on state-level average employer premiums for individuals and families from the MEPS Insurer/Employer Component (MEPS-IC).<sup>34</sup> We also rely on the employer subsidies from the MEPS-IC. Lastly, we reduce the cost of employer premiums based on the family's marginal tax rate, to account for the tax deductibility of employer premiums.

## Module 8: Coverage

### Overview

We determine each individual's coverage option based on a utility framework. We assign a utility to different combinations of coverage choices within a family, and the family selects the configuration of coverage choices corresponding to the highest utility. We perform this coverage determination in five steps:

1. We specify a utility function that accounts for expected health care consumption, expected cost to the family, and financial risk.
2. We calculate family-level utilities for different combinations of coverage choices.
3. We determine each family member's coverage choice by identifying the configuration of coverage choices that maximize the family's total utility.
4. With a new set of coverage decisions, we recalculate premiums based on the updated risk pools.
5. We repeat steps one through four until the model reaches an equilibrium.

### Approach

We calculate utility based on same utility function used by the RAND COMPARE microsimulation model.<sup>35</sup> RAND calibrated this function to replicate both empirical coverage take-up rates and price elasticities from the health economics literature. We calculate utility as follows:

Utility =	30% of expected health care consumption	–
	100% of annual health insurance premiums	–
	100% of expected annual out-of-pocket costs	–
	0.0232% of annual variance in out-of-pocket costs	+
	Calibration factors	

### Expected Health Care Consumption

An individual's utility from a coverage option is higher if that person would be able to consumer more services under that coverage option. We denominate health care consumption in dollars by multiplying expected utilization under the coverage option by commercial unit prices. For purposes of computing this term of the utility function, we do not incorporate region- or payer-specific price variation. Therefore, measured variation in healthcare consumption is driven by differences in utilization of services, rather than differences in prices paid. In our model, utilization rates do not vary among those with insurance coverage but do vary between the insured and uninsured. Thus, differences in consumption across coverage options can be interpreted as the value to the individual of additional

<sup>34</sup> Insurance/Employer Component. Agency for Healthcare Research and Quality. <https://bit.ly/2HjRaus>.

<sup>35</sup> Establishing State Health Insurance Exchanges. RAND Corporation. 2010. Available at <https://bit.ly/2Twp727>.

services consumed due to having health insurance. Like RAND, we assume that a family derives utility from 30% of their health consumption.

#### Premiums, Expected OOP and Variance OOP

We assume that utility decreases for a coverage option as health insurance premiums, expected OOP and variance OOP increase. The expected OOP and premium represents the expected cost to the family of that coverage option. The variance OOP represents the financial risk to the family of the coverage option. We calculate mean OOP and variance OOP through a Monte Carlo simulation. We simulate many instances of OOP, and compute the mean OOP and variance OOP across those simulated values at the family-level. Following RAND COMPARE, we multiply variance in out-of-pocket costs by 0.0232%. For purposes of calculating utility, we only consider the portion of insurance premiums paid by the family. We discount premiums to account for income-based premium subsidies and employer subsidies, as appropriate. We also discount ESI premiums to account for employee's ability to buy plans with pre-tax dollars.

#### Calibration Factors

We include several calibration factors to produce modeled 2017 insurance take-up rates that match empirical ACS take-up rates overall and by income group, racial/ethnic group, and age. For example, we reduce the value of health insurance coverage for Hispanic individuals to account for lower health insurance take-up rates among the Hispanic population. We calibrated our model to forecast non-group coverage take-up among those not enrolling in ESI or public coverage. We recently expanded our model to simulate coverage choices for those enrolled in ESI at baseline. If a respondent reports being on ESI in the ACS, we assign a calibration factor such that their ESI utility is at least as high as any other coverage option in our baseline scenario.

#### Coverage Configurations

We calculate utility at the family level under nearly every permutation of family member coverage choices. We exclude certain configurations on the basis of eligibility. For example, dependents cannot choose ESI if the would-be ESI policyholder chooses another option. Additionally, we do not consider scenarios where families choose multiple family health plans. For example, in a family of four, we would allow two family members to choose an ESI plan while the other two family members choose to be uninsured. However, we would not allow two family members to choose a family ESI plan and two family members to choose a non-group plan. To reduce computational complexity, we exclude families with more than five members from the simulation. This simplification results in a loss of approximately 3% of our sample. We adjust respondent weights to account for this loss.

After families make coverage choices, premiums are recalculated based on the new risk pools, and families update their choices based on the updated premiums. This process repeats until we reach equilibrium.