KNG Health Reform Model: Technical Report

Version 2.0

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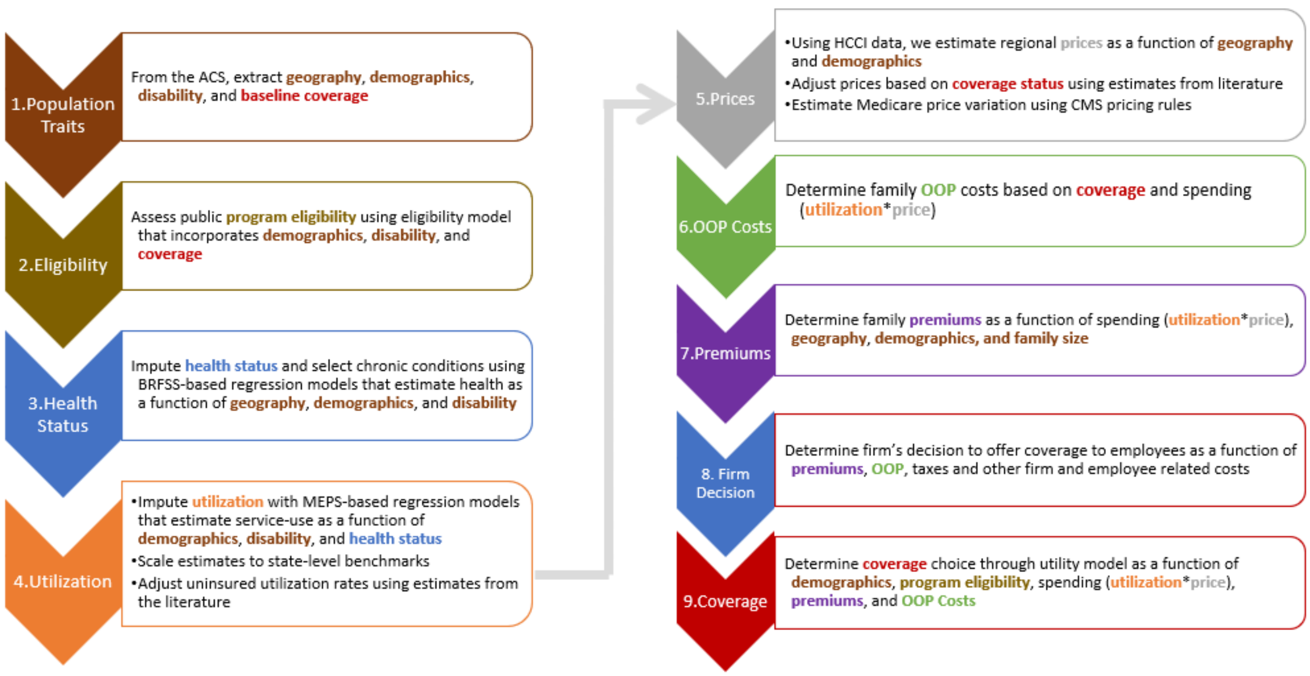
Contents

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 model starts with a nationally representative sample of households from the American Community Survey (ACS) and proceeds to simulate coverage by moving through nine 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 nine Modules included within the KNG-HRM



Notes: ACS = U.S. Census Bureau American Community Survey; BRFSS = CDC Behavioral Risk Factor Surveillance System; MEPS = AHRQ Medical Expenditure Survey; HCCI = Health Care Cost Institute; OOP = out-of-pocket.

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 through 2032. 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.
2. We develop a population projection file that combines national projections from the U.S. Census with state-specific projections.
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).[1] We obtained the 2018 ACS from the IPUMS website.[2] 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)[3];
- 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 2018 to 2060.[4]

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[1] American Community Survey. United States Census Bureau. 2017. Available at https://bit.ly/1M2wMJQ.

[2] 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

[3] 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.

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

State-Based Population Projections

We supplemented the US Census demographic projections with additional projections by state, gender, and age available from the University of Virginia Cooper Center.

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.

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 using state, gender, and age adjustments by decade available from the University of Virginia Cooper Center.

Projecting the ACS File Forward

We used our population projection growth rates to develop annual growth rates by year for each single age, sex, state, race, and ethnicity combination. We projected the 2018 ACS forward by linking each respondent to the appropriate growth rate and multiplying this growth rate by their population weight.

Benchmarking Baseline Insurance Coverage Status

There are too few respondents in the ACS indicating that they are enrolled in Medicaid, relative to benchmarks based on administrative data. We rebalance the population between coverage groups by reassigning to Medicaid a portion of the overages in the other coverage categories up to the benchmark for Medicaid.

Seven states (Virginia, Maine, Idaho, Utah, Nebraska, Oklahoma, and Missouri) recently approved Medicaid expansions under the ACA. However, those expansions are not reflected in the 2018 ACS survey. For those states, we reassign a portion of the state's population to Medicaid coverage based on impacts estimated by The Urban Institute[5].

[5] For Nebraska, Oklahoma and Missouri: https://www.urban.org/sites/default/files/publication/102359/the-implications-of-medicaid-expansion-in-the-remaining-states-2020-update_1.pdf. For Virginia, Maine, Idaho, Utah: https://www.urban.org/sites/default/files/publication/98467/the_implications_of_medicaid_expansion_2001838_2.pdf.

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 for immigrants. 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 ACA premium cap used for determining Marketplace subsidies.

Data

<u>Medicaid/CHIP Eligibility Limits</u>

The Kaiser Family Foundation (KFF) publishes state-specific income eligibility thresholds for children, parents, pregnant women, and other adults.[6] These thresholds can be compared with family income levels to assess Medicaid eligibility.

<u>U.S. unauthorized immigrant population estimates by state</u>

The Pew Research Center (Pew) publishes state-specific estimates for the percent of the foreign-born population that is unauthorized.[7] 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:

MAGI =		Wage and Salary Income
	+	92.35% of Business and Farm Income
	+	Interest, dividend, and rental income
	+	Retirement Income
	+	Social Security Income

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.[8]

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[6] Trends in Medicaid Income Eligibility Limits. Kaiser Family Foundation. https://bit.ly/2Gpp29q.

[7] U.S. unauthorized immigrant population estimates by state, 2017. Pew Research Center. http://www.pewhispanic.org/interactives/u-s-unauthorized-immigrants-by-state/

[8] 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.

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 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 the likelihood of giving birth in the next 12 months for each female respondent in the ACS between the ages of 19 and 45.

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.

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 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 affordable employer coverage, and must not be an undocumented immigrant. 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 2.07% to 9.83% in 2021.[9] 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:

[9] IRS Rev. Proc. 2020-36. Available at: https://www.irs.gov/pub/irs-drop/rp-20-36.pdf.

1. We estimate incident rates of different health indicators using regression analyses based on data in the 2018 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

<u>Behavioral Risk Factor Surveillance System (BRFSS)</u>

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 states and the District of Columbia. They 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.

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 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 five 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 perform a 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).
5. We developed a methodology to increase intrapersonal correlation across service categories to empirically observed levels.

Data

<u>Medical Expenditure Panel Survey (MEPS)</u>

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.

<u>Annual Health Care Cost and Utilization Report (HCCUR)</u>

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 2017 HCCUR file for national utilization levels for those covered by commercial insurance.

HCCI ER Spending, Use, and Price Trends

HCCI has released an Excel report on state-level variation in ER spending, utilization, and price between 2013 and 2017. ER visits are defined by current procedure terminology (CPT) codes 99281-99285.

We used the 2017 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.[10] 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 2017 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.

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 covariates shown in Figure 2.

[10] Trends In Primary Care Visits. Health Care Cost Institute. Available at https://bit.ly/2zSNryw.

Figure 2. Covariates Used in MEPS Utilization Model

Category	Variables
Demographics	Sex, age, race, and geographic region
Family Structure	Family size and marital status
General health status	Reported general health as excellent, very good, good, fair, or poor
Disability	Difficulty with vision, hearing, ambulation, cognitive, self-care, and/or independent living
Healthy Behaviors	Smoking status
Chronic conditions	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[11]:

- **Hospitalizations** increased by 30%
- **ER visits** increased by 40%
- **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 to estimate that a person with insurance would have 34% more hospital outpatient visits than if that person was uninsured.

[11] 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
$Y_i \sim$ Poisson(μ_i) with probability $1-P_i$

To simulate from this distribution, we require P_i (the probability of having any utilization) and μ_i (the conditional mean utilization). Both parameters were 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(μ_{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.

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 2018 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.[12] The HMI is designed to compare "the prices paid for the same set of services for largely similar populations across areas."[13] 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.[14]

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.[15]

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.[16]

Approach

National Price Levels by Payer

We extracted national 2017 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

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[12] Healthy Marketplace Index. Health Care Cost Institute. Available at https://www.healthcostinstitute.org/research/hmi.
[13] 2018 Healthy Market Place Index Frequently Asked Questions. Health Care Cost Institute. Available at https://bit.ly/2BMdKav.
[14] FY 2016 Final Rule and Correction Notice Data Files. Centers for Medicare & Medicaid Services. Available at https://go.cms.gov/2s0L2hQ.
[15] FY 2016 Final Rule. Centers for Medicare & Medicaid Services. Available at https://go.cms.gov/2U49g74.
[16] CY 2016 Final Rule. Centers for Medicare & Medicaid Services. Available at https://go.cms.gov/2TgeYFP.

Health Care Cost Institute (HCCI), CBO found that commercial insurers paid 89% more than Medicare for inpatient hospitalizations.[17] The findings were similar for both medical and surgical admissions.

CBO also found that commercial insurers paid more than Medicare for physician services but did not report an overall average difference.[18] 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.[19] 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.

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."[20] 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.[21] This is consistent with public filing reports from California insurers which showed commercial outpatient rates that were 200% more than Medicare.[20] The American Hospital Association reports aggregate hospital payment-to-cost ratios by payer, which reflect both inpatient and outpatient services.[22] 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.[23] 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.[24] Our own analysis of financial data from the AHA Annual Survey showed similar hospital payment-to-cost ratios for uninsured and Medicare patients.

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[17] 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.

[18] 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.

[19] HCCI Professional Service Categories – CPT Procedure Codes. Health Care Cost Institute. 2016. Available at https://www.healthcostinstitute.org/research/research-resources.

[20] 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

[21] 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/.

[22] 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.

[23] 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.

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

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 3 shows the prices we used by payer in each service category.

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. If the nearest CBSA is more than 100 miles away, we assign the average HMI for the geographic region.

Regional Medicare Prices

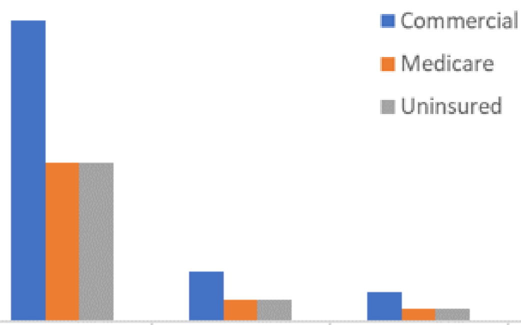
To estimate regional Medicare prices, we estimated service-specific Medicare price indices based on the payment parameters used by CMS when determining reimbursement. For inpatient services, the regional index value was based on the CMS wage index adjustment, cost-of-living adjustment, disproportionate 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 from IQVIA. This report shows the national total number of retail prescription drugs filled at pharmacies, and associated spending.[25] We used these data to estimate a national price per filled prescription of $108.68. We did not vary this price by payer, geography, or patient type.

[25] Health Costs & Budgets Indicators – Prescription Drugs. Kaiser Family Foundation. Available at https://bit.ly/2Hpo2lm.

Figure 3. Assumed national average prices in each service category by payer



	Hospitalizations	Outpatient Visits	Emergency Room Visits	Physician Visits
Commercial	$21,261.23	$3,521.75	$2,039.26	$117.67
Medicare	$11,249.33	$1,565.22	$906.34	$78.97
Uninsured	$11,249.33	$1,565.22	$906.34	$117.67

Commercial Medicare Uninsured

Source: KNG Health analysis of 2017 HCCI Annual Report file

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:

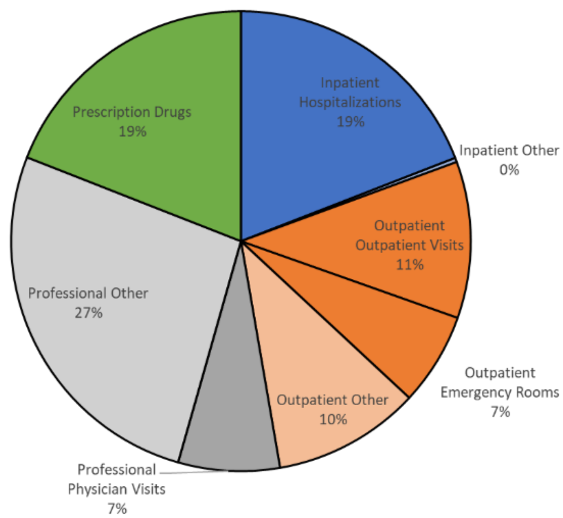
1. We calculated healthcare spending by multiplying simulated utilization counts by corresponding unit prices and adjusted for categories of spending not encompassed by our service categories.
2. We identified national average deductibles, out-of-pocket maximums, and actuarial value for different types 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

<u>Estimating Individual Health Spending</u>

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 heath spending is for either outpatient hospital services (e.g., ancillary, laboratory, and radiology) or professional services (e.g., anesthesia, surgery, drug administration).

Figure 4. 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:

Spending =	Other spending adjustment *				
		(	Hospitalizations	* Hospitalization Price	+
			Outpatient Visits	* Outpatient Visit Price	+
			ER Visit	* ER Visit Price	+
			Physician Visit	* Physician Visit Price	+
			Prescription Drug Filling	* Prescription Drug Filling Price	)

On average, the other spending adjustment was the reciprocal of 58.9%, but we allowed this adjustment to vary by age and sex.

Estimating OOP Spending

Figure 5 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.[26,27] 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).[28] We assumed these parameters applied to all individuals enrolled in that coverage type.

[26] 2018 Employer Health Benefits Survey. Kaiser Family Foundation. October 2018. Available at https://www.kff.org/report-section/2018-employer-health-benefits-survey-section-7-employee-cost-sharing/
[27] Average Market Premiums Spike Across Obamacare Plans in 2018. HealthPocket. October 2017. Available at https://bit.ly/2XKY6pU
[28] The Budget and Economic Outlook: 2018 to 2028. Congressional Budget Office. August 2018. https://www.cbo.gov/publication/54318.

Figure 5. Assumed 2018 Individual/Family Deductibles and OOP Maximums

Cost-Sharing Parameter	ESI	Marketplace
Individual Deductible	$1,573	$4,033
Individual OOP Maximum	$3,872	$6,863
Family Deductible	$3,671	$8,292
Family OOP Maximum	$6,710	$13,725

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.[29] 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.[30] 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 10%. We assumed non-group market enrollees would pay a pre-deductible coinsurance rate of 40% and a 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 and ESI 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 six steps:

1. For non-group premiums, define state-specific risk pools that consist of all individuals who enroll within the state. For ESI premiums, we combine all small firms (less than 50 employees) in a state into one risk pool, while each large firm is its own separate risk pool.
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.

[29] 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/.
[30] Consumer Cost-Sharing in Marketplace vs. Employer Health Insurance Plans. December 2015. Available at https://bit.ly/2VGtRio.

5. Scale employer plan prices and utilization so that premiums match state average premiums reported in the MEPS.
6. Scale non-group plan prices and utilization so that premiums match state benchmark premiums.

Approach

Using the methodology described in Module 6, we can simulate health spending and OOP for individuals electing to enroll in non-group and ESI 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.

For non-group coverage, we extracted state specific administrative load from Medical Loss Ratio data filed by insurers.[31] For ESI coverage, we impute an administrative load for each firm based on firm size using estimates reported by RAND.[32] We scale the imputed administrative burden to be 12%, the private health insurance expenditure estimates reported in the National Health Expenditure Accounts.[33]

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.[34] Premiums can also be up to 50% higher for tobacco users, though the exact rating difference varies by state. Using these rules, we assign a rating factor to each individual enrolling in 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 and those considering enrolling in coverage.

We scale ESI prices and utilization such that our calculated ESI premiums benchmark to state-level average employer premiums for individuals and families from the MEPS Insurer/Employer Component (MEPS-IC).[35] We also rely on the MEPS-IC to assign employer subsidy percentages. 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.

Following the federal defunding for cost-sharing reductions, issuers priced the value of those reductions directly into the premium of benchmark silver plans, a practice known as "silver loading". This inflated premiums for benchmark silver plans but had the advantage of increasing the value of premium tax credits. We accounted for the impact of silver loading by attributing half the difference between the benchmark silver plan and the lowest priced bronze plan (from KFF) to silver loading by issuers. We inflate non-group premiums by 100% minus the silver loading percentage and then scale NOG prices and utilization so that our NOG premiums match the state benchmark silver plan.

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[31] https://www.cms.gov/CCIIO/Resources/Data-Resources/mlr

[32] Eibner, C., Girosi, F., Miller, A., Cordova, A., McGlynn, E. A., Pace, N. M., ... & Gresenz, C. R. (2011). Employer self-insurance decisions and the implications of the Patient Protection and Affordable Care Act as modified by the health care and education reconciliation Act of 2010 (ACA). Rand health quarterly, 1(2). Available at: https://www.rand.org/pubs/technical_reports/TR971.html.

[33] 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.

[34] Market Rating Reforms. Centers for Medicare & Medicaid Services. https://go.cms.gov/2EGTRDd.

[35] Insurance/Employer Component. Agency for Healthcare Research and Quality. https://bit.ly/2HjRaus.

Module 8: Firm Decision

The ACS indicates whether respondents are employed but does not include information on the size of the firm where they are employed. Because employer insurance varies significantly by firm size, we used the Current Population Survey (CPS, 2016-2018) data to impute firm size. Firms were classified into 5 firm size categories: (1) fewer than 10 workers; (2) 10 to 49 workers; (3) 50 to 100 workers; (4) 100 to 999 workers; and (5) more than 1,000 workers. We started by running a multinomial logistic regression to estimate the size of the firm where each of the CPS respondents works. We then used the estimated coefficients from that model to impute firm size for the observations in the ACS. We calibrated the imputed ACS private sector firm size to match the state level distribution in the MEPS-Insurer/Employer Component (IC).

We assigned each ACS worker's initial firm offer status using various MEPS-IC tables (by firm size, industry, and income quartile) and adjusted as necessary to ensure consistency between ESI offer and ESI enrollment. Next, we combined the ACS workers into synthetic firms based on the following hierarchy of characteristics: offer status, firm size, industry, region, and state. We treated all federal government employees as working for the same firm. We treated other government employees residing in the same state as being employed by the same firm. We also assumed that all local, state, and federal government employees have access to ESI coverage and work in a firm with more than 1,000 employees.

Overview

To model a firm's decision to offer ESI access to their employees under alternate policy scenarios, we perform the steps below:

1. Evaluate premiums, out-of-pocket costs, financial penalties, and other costs.
2. Define the savings to a firm and its employees from dropping coverage as the difference in savings between a scenario where the firm offers coverage and a scenario where the firm does not offer coverage.
3. If these savings exceed a minimum savings threshold, assume the firm drops coverage.

Approach

While simulating an alternate policy scenario, if a new coverage option becomes more desirable than the existing coverage available through employer then individuals might opt out of ESI coverage. This can push employers to reconsider the continuation of ESI offer to all employees. If the employer and the employees in a firm are overall better off with a new coverage option, then the firm may decide to drop coverage. The factors we assumed are considered by firms in estimating savings to the firm and its employees are listed in Figure 6.

Figure 6. Description of Components in Firm Cost Model

Cost Component	If the employer maintains coverage…	If the employer drops coverage…
Premiums for workers and dependents, net of subsidy	The sum of: • The employee's and employer's share of ESI premiums for those taking up ESI coverage, reduced by the enrolling family's marginal tax rate; and • Net premiums for those opting out of ESI coverage.	Marketplace net premiums for all workers and dependents.
Out-of-Pocket Costs	Out-of-pocket health costs for workers and dependents either participating in the ESI plan or receiving coverage through non-group coverage.	Out-of-pocket health costs for workers and dependents receiving coverage through non-group coverage.
Financial Penalties	None.	For applicable large firms, shared responsibility payment per the ACA.
Other Costs	The internal HR administrative burden of offering coverage.	None.

In our current model, we assume a firm drops coverage if the savings resulting from dropping coverage (net of costs associated with dropping coverage) are higher than 7 percent of the total payroll of the firm. We establish the threshold at 7 percent because, at this threshold, most firms who are currently offering ESI would offer ESI based on our model prediction.

We model the firm decision through an iterative process by allowing the employee's coverage decision to feedback into the firm's decision. With everyone making a choice, the risk pool for each coverage type changes, which leads to premiums adjusting dynamically. The firm uses these updated premiums in re-evaluating the decision to offer coverage. This process continues till the model reaches an equilibrium.

Module 9: Coverage

Overview

We determine everyone's coverage option based on a utility framework. We assign a utility to different combinations of coverage choices within a household, and the household 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 a utility function used by the RAND COMPARE microsimulation model.[36] 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	–
		r_{year}% 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 consume 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 services consumed due to having health insurance. Like RAND, we assume that a family derives utility from 30% of their health consumption.

[36] Establishing State Health Insurance Exchanges. RAND Corporation. 2010. Available at https://bit.ly/2Twp727.

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 premiums represent 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. We calculate the coefficient on the variance OOP by inflating the empirical estimates from Manning and Marquis (1996)[37] based on NHE expected changes in out-of-pocket costs. 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

To ensure the accuracy of coverage and utilization predictions in KNG-HRM, we first estimate a coverage decision model in the status-quo. For individuals and households whose coverage decisions depart from their "observed" coverage choice in the ACS, we calibrate the utility maximization function so that the predicted decision matches the status-quo decision for everyone. We calculate the calibration term as the difference in utils a household receives from choosing the observed coverage versus the utils received in the estimated choice. This difference is scaled to maintain distributional similarity with the households which do not require any calibration. The calibration terms generated in this step are carried forward in any alternative policy scenario to incorporate consistency in decision making.

Coverage Configurations

We calculate utility at the family level under nearly every permutation of family member coverage choices. We exclude certain configurations based on 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 six 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.

[37] Manning W and Marquis S, "Health Insurance: The Tradeoff Between Risk Pooling and Moral Hazard," Journal of Health Economics, Vol. 15, No. 5, 1996, pp. 609–639.