Health Cost Landscape

Technical Appendix

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April 2026

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Introduction

Health care spending in the United States has risen dramatically over recent decades and is projected to continue growing into the future. While this trend holds nationally, there is an increasing body of evidence that the sources of both health care spending levels and growth vary dramatically across the country. It is therefore important to understand the factors associated with health care spending in different areas, and how these factors have and may continue to change over time.

The Health Cost Landscape (HCL) reports a series of metrics which can be used to assess the economic performance of local commercial health care markets. These metrics are intended to facilitate comparable and consistent assessments of health care market performance both across markets and within markets over time. These metrics are additionally intended to be transparent, both in their availability through public use files, and in their construction through comprehensive methodological documentation.

This document describes how we use the Health Care Cost Institute (HCCI) commercial claims database to construct our HCL metrics. From HCCI data, we constructed a sample containing the health care claims for individuals receiving commercial health insurance through their employer in the years 2018 and 2022, residing in one of our 269 sample metro areas across 45 states and the District of Columbia. These data contain more than 1.3 billion claims from 2018 and 2022 from more than 38 million individuals annually.

Using our analytic sample of claims, we constructed indices of metro area health care spending ("Spending Index"), health care cost burden ("Cost Burden Index"), average health care service prices ("Price Index"), volume of health care services used ("Use Index"), and the cost of the mix of services used ("Service Mix Index"). We constructed each of these metrics both at a metro area level, as well as by high level service category (Inpatient, Outpatient, Professional Services) in each metro. Separately, we also constructed a measure of inpatient hospital market concentration for each metro area ("Concentration Index").

We gratefully acknowledge financial support for this project from Arnold Ventures.

1. Using HCCI Claims Data to Construct an Analytic Sample of Claims

Using HCCI claims data, we constructed a sample of health care services provided in geographic areas across the country in each year. The HCCI claims data are primarily organized at the claim line level. That is, for a service performed, the claim file is broken up into multiple claim lines (e.g., one claim line for a particular lab, another for a procedure). To construct a service level sample from the claim line level data, we aggregated data from all claim lines associated with each service to the claim level. This aggregated service will be referred to as a service claim. Our analytic sample consisted of cleaned service claims from enrollees residing in our sample geographic regions (regardless of where services were provided).

1.1 Defining a Sample Population of Members

Using monthly enrollment data, we constructed a sample of member-month observations. For a member month to be included in the sample population, the member, in that given month, must be under the age of 65 and have an identifiable age and gender in the data. We also limited our sample of member-months to individuals with an identifiable five-digit zip code. Further, we excluded member-months in which the individual resided in two or more metro areas in the same month.

Additionally, we restricted our analysis to member-months for individuals with coverage through an employer-sponsored insurance (ESI) plan. Specifically, we limited our sample to individuals with either small or large group commercial insurance coverage with one of the following plan types: Health Maintenance Organization, Preferred Provider Organization, Point of Service Plan, or Exclusive Provider Organization.

1.2 Assigning Member-Months to Core-Based Statistical Areas

Our geographic unit of analysis was the Core-Based Statistical Area (CBSA). Using monthly enrollment data, we mapped the five-digit zip code associated with each member-month to a CBSA. Because CBSA definitions change over time, we used a fixed five-digit zip-code-to-CBSA crosswalk regardless of the year so that a CBSA in our data refers to the same geographical region across time.

To construct our geographic crosswalk, we used a five-digit zip-code-to-CBSA crosswalk constructed by the United States Department of Housing and Urban Development (HUD) from our base year (2022). In cases where a zip code is assigned to multiple CBSAs, we assigned zip codes to the CBSA with the greatest “Total Ratio” followed by the greatest “Residential Ratio.”

Member months associated with zip codes that did not match a CBSA from the crosswalk were omitted. Member-months whose zip codes matched to areas outside of the 50 United States or DC were also omitted. Altogether over 82% of member months were included in the final analytic sample.

Counts of member-months were generated at the CBSA-year and state-year level to be used for per-person spending and use calculations.

1.3 Aggregating Claim Lines to Claim level

Prior to aggregating claim lines, we merged on enrollment information based on the month and year in which a claim line occurred – as defined by the dates associated with each claim line. We excluded all claim lines associated with member-months that were not part of our sample population. We assigned each claim line to the CBSA and state associated with the five-digit zip code attached to the relevant member month.

We defined a service claim as all claim lines for an individual with common dates and service codes. We defined service codes distinctly in each high-level service category (inpatient, outpatient, and professional). For inpatient claims, we defined a service code as Diagnosis Related Group (DRG) codes. For outpatient and professional claims, we defined service codes as Healthcare Common Procedure Coding System (HCPCS) codes.

When aggregating claim lines to the service claim level, we summed all allowed amounts (the actual amount paid for the claim) from each claim line associated with a particular service claim. Allowed amounts comprise the insurer’s payment to a provider and the patient’s out-of-pocket payment. We defined the sum of the these allowed amounts as the total spending on a service claim.

1.4 Cleaning Claims to Construct the Analytic Sample

We applied separate cleaning procedures to inpatient, outpatient, and professional service claims.

Inpatient Claims (Admissions)

Our unit of analysis for inpatient service claims was an inpatient admission defined by a combination of year, patient, service code (DRG), and admission and discharge dates.

We identified the inpatient facility associated with each claim by encrypted National Plan and Provider Enumeration System Identifiers (NPI) and room and board revenue charge. Admission and discharge dates were calculated as dates of contiguous claims with room and board charges. We assigned DRG and total allowed amounts, facility inpatient price, among service from dates of facility claims that fell between admission and discharge dates. We assigned a single DRG to each inpatient admission based on highest total allowed amounts, then highest total out-of-pocket amounts for tiebreakers. A small proportion of inpatient admissions had evidence of multiple DRGs (e.g., complications during course of inpatient stay).

Claims were excluded with allowed amounts less than 1 dollar. We limited to inpatient admissions where health plan was the primary payer and to inpatient admissions rendered at general acute care hospitals. Additionally, we excluded inpatient admissions where the enrollee did not have evidence of active ESI enrollment on admission date.

Using each facility identifier (NPI), we merged on hospital characteristics from the American Hospital Association (AHA) in each year among general acute care (GAC) hospital respondents.

Outpatient Claims (Procedures / Visits)

Our unit of analysis for outpatient claims was the visit or procedure defined by the combination of year, patient, visit dates, HCPCS code level.

Claims with allowed amounts less than 1 dollar were excluded. Additionally, claims in which the ESI plan was not the primary coverage payer were excluded. Claims that did not have a corresponding ESI enrollment record during the service date were also excluded.

Professional Claims (Procedures / Visits)

Our unit of analysis for professional claims was the visit or procedure defined by the combination of year, patient, visit dates, and HCPCS code level.

Claims were excluded if the HCPCS code was missing and could therefore not be assigned a service code. Additionally, claims in which the ESI plan was not the primary coverage payer were excluded. Claims that did not have a corresponding ESI enrollment record during the service date were also excluded.

Geographic inclusion criteria

We applied masking and inclusion rules to claims data prior to conducting analysis for HCL. For a year-geography-service combination to be included in the final analytic data set it had to meet the following criteria:

1. The member geography had at least 10,000 member years of enrollment in both 2018 and 2022.

2. The HCCI enrollment data captured at least 10% of the ESI population measured in the American Community Survey for the geography.
3. The HCCI claims for the geography had at least five unique providers.
4. The geography had a minimum of 400 inpatient claims in 2018 and 2022.
5. The geography had a minimum of 500 outpatient claims in 2018 and 2022.
6. The geography had a minimum of 500 professional claims in 2018 and 2022.

The final analytic file included 269 Core-based Statistical Areas (CBSAs) and 45 states. The national data we used in subsequent analysis used data from all 269 CBSAs and 45 states and did not include data from geographic units that did not meet the inclusion criteria.

Summary Statistics of our Analytic Sample

Our analytic sample includes more than 1.3 billion claims from years 2018 and 2022 across more than 62 million member years. This includes an average of more than 1.3 million inpatient claims, 110 million outpatient claims, and 560 million professional claims, annually. These claims are attributed to an average of more than 38 million individuals annually.

Our analytic sample comprises a consistent subset of all HCCI claims across our study period. As seen in Table 1.1, our sample includes 67% of the universe of HCCI claims in each year, and about 74% of total spending (defined as the sum of allowed amounts). Our analytic sample captures a slightly higher percentage of professional claims (70% of claims) than inpatient and outpatient claims (between 57% and 59% of claims).

Table 1.1 Share of HCCI Universe of Claims, Spending Included in Analytic Sample by Year

Service Category	2018	2022
Share of Claims		
Overall	67%	67%
Inpatient	58%	59%
Outpatient	58%	59%
Professional	70%	69%
Share of Spending (Total Allowed Amounts)		
Overall	73%	74%
Inpatient	72%	72%
Outpatient	70%	71%
Professional	77%	79%

2. Constructing Spending, Use, Price, Service Mix, and Cost Burden Indices

We used the inpatient (IP), outpatient (OP), and professional (PH) claims in our analytic dataset to compute aggregated measures of spending, price, use, service mix, and cost burden. We conducted analysis at three geographic levels; Core-Based Statistical Area (CBSA), state, and national. All measurements and analysis were performed separately for two years of data, 2018 and 2022.

In this section, we describe how we aggregated the claims data into an analytic dataset of spending, price, and use variables specific to each service, geography, and year. Each service is unique to a category, defined based on the type of claim (IP, OP, PH). The summary data are the basis for calculating measures of spending, prices, use, and service mix at the geography-year-category-level. We then converted the measures into index values, which are reported on the HCL website, and aggregated category index values into an overall index.

2.1 Using claims to measure spending, price, and use

Classifying Claims

Each claim in the analytic sample described in Section 1.4 is identified by a year, geography, and service. HCCI has a nesting scheme that assigns services to sub-categories and categories based on the Diagnosis Related Group (DRG) for inpatient claims, or the restructured Berenson-Eggers Type of Service (BETOS) code for outpatient and professional claims.

Table 2.1 lists the dimensions used to group claims together, a notational convention used to refer to the dimension throughout this document, and a brief description of the dimension.

Table 2.1: Claims classification system

Dimension	Notation	Values	Description
Time	t	2018, 2022	Claims are assigned to a year based on the date they were incurred.
Geography	g	National, State, CBSA	The geography of measurement. Claims are assigned to a geography based on the member's ZIP code. Each claim in the analytic data is assigned to both a CBSA and a State. All claims in the analytic file are

			considered part of the National geography.
Service Category	c	Inpatient, Outpatient, Professional	Each claim is assigned to one service category based on its claim type.
Service Sub-category	k	Major Diagnostic Category (IP), BETOS Code (OP, PH)	Each claim is assigned to one sub-category nested within its service category. Sub-categories are defined as the combination of Major Diagnostic Category (MDC) and medical/surgical flag for the IP file. Sub-categories are defined by Restructured BETOS codes for the OP and PH files.
Service	s	DRG (IP), HCPCS Code (OP, PH)	Each claim has one service code that nests within a sub-category and a category. This is the most granular level of classification used in the HCL methodology.

Claims are assigned to a category based on cleaning rules described in Section 1.4. Once a claim has a category, we used the service on the claim to assign it to a service and a sub-category within the overall service category. The service codes for inpatient claims are Diagnosis Related Groups (DRG) and the service codes for outpatient and professional claims are Healthcare Common Procedure Coding System (HCPCS) codes. Note that the universe of HCPCS codes includes Current Procedural Terminology (CPT) codes.

We used an existing classification system maintained by HCCI to group services into sub-categories. For inpatient claims, the sub-category is the combination of the Major Diagnostic Category (MDC) and Medical/Surgical flag associated with each DRG. The MDC code describes the body system or procedure type of the DRG and the Medical/Surgical flag indicates the type of procedure.

The sub-categories for outpatient and professional claims were assigned separately but use the same system. HCCI maintains a proprietary crosswalk linking each HCPCS code to a Restructured Berenson-Eggers Type of Service (BETOS) code. BETOS codes group HCPCS codes into broad categories of similar services and were originally designed for describing Medicare expenditure growth.

In addition to the classification variables above, we assigned each claim in the analytic sample two attributes, an allowed amount and a use amount. The allowed amount comes directly from the claims data and represents the actual transaction between the payer and provider for the claim. We defined the use amount of each claim as 1.

Because the HCCI data represent a sub-sample of all ESI members and claims, we applied weights to each claim so that our analysis would be reflective of the national non-elderly population with ESI.

We calculated population weights using the American Community Survey (ACS) 2022 5-year estimates Public Use Microdata Sample (PUMS) to develop estimates that were representative of the national ESI population younger than 65. In order to account for heterogeneity of enrollment trend by demographics, weights were estimated at enrollee's age band-sex-year-geographic unit. We leveraged geographic crosswalk from the Missouri Census DataCenter at the University of Missouri to merge ACS data to HCCI enrollment record by zip codes/ZCTA and PUMA-state code. Note: Standard residential zip codes and ZCTAs are identical.

$$ESI\ Weights_{y,s,g,a} = \frac{Number\ of ESI\ enrollees\ from\ ACS_{y,s,g,a}}{Number\ of\ ESI\ enrollees\ from\ HCCI\ _{y,s,g,a}}$$

Where:

- *y denotes calendar year*
- *s denotes sex*
- *g denotes PUMA-state geography*
- *a denotes age band code.*

We multiplied the allowed amount and use amount of each claim by the ESI weight to produce the following variables for each observation (*i)* in the analytic sample:

$$Allwd_{igts} = AllowedAmt_{igts} * \ \omega_{gt}$$
$$Use_{igts} = UseAmt_{igts} * \ \omega_{gt} = \ \omega_{gt}$$

Note that because $UseAmt_{igts}$ is equal to 1 for all claims by construction, this means that the Use_{igts} associated with a single claim is equal to the ACS weight of the patient, ω_{gt}.

Aggregating claims to service-level measures

We used a summary file of the claims data as the basis for HCL measures and calculations. The summary file aggregates the claims data into a file where each row is a geography-year-service combination. This means there is an observation for each service (s) in 2018 and 2022 (*t)* for each CBSA, State, and National geographic unit (*g*).

We aggregated the claims-level data by summarizing the total spending, total use, and four measures of price for each service. The equations below formally describe the summary calculations. Note that when referring to service-level measure (s) we exclude the category (c) and subcategory (k) to streamline notation, but each service is nested within a service category (*c*) and sub-category (*k*).

Total spending (y_{gts}) is the sum of all weighted allowed amounts for claims with service code s, within geography *g*, incurred during year *t*. The notation $i \in gts$ means that claim *i* is for geography *g* in year *t* and service *s*:

$$y_{gts} = \sum_{i \in gts} Allwd_i$$

Total use (u_{gts}) is the sum of all weighted use amounts for claims with service code *s*, within geography *g*, incurred during year *t*:

$$u_{gts} = \sum_{i \in gts} Use_i$$

In addition to price and use, we calculated four summary measures of price for each observation: the 25th percentile price, the 50th percentile (median) price, the 75th percentile price, and the average (mean) price within each geography and year. We used the unweighted allowed amount when calculating the price measures.

$$p_{gts}^{x} = f^{x}(AllowedAmt_i) \; where \; i \in gts$$

In this notation, *x* refers to the four statistical calculations of interest (25th percentile, 50th percentile, 75th percentile, mean) so that $f^x()$ indicates taking the 25th percentile, median,75th percentile, and mean of all unweighted allowed amounts on claims for service *s* in year *t* and geography *g*.

The spending and use variables in the summary file are raw sums, meaning they are sensitive to the number of enrollees in geography *g* in year *t*. We normalized spending and use measures by converting them to per-member-per-year (PMPY) scale. We joined the number of member-months in each geography-year calculated in Section 1.2 to the summary data on the year and geographic identifier and converted member-months to member-years (m_{gt}) by dividing by 12. We used the m_{gt} measure to calculate PMPY spending (y_{gts}^{pmpy}) and PMPY use (u_{gts}^{pmpy}) as:

$$y_{gts}^{pmpy} = \frac{y_{gts}}{m_{gt}}$$

$$u_{gts}^{pmpy} = \frac{u_{gts}}{m_{gt}}$$

2.2 Aggregating Services into Sub-Categories

We used the service level summary file (Section 2.1) to calculate measures at the sub-category-year-geography level. Each observation in this file represents a spending, use, or price measure for a specific sub-category of services in a single geographic area in either 2018 or 2022.

The service-level PMPY spending (y_{gts}^{pmpy}) and use (u_{gts}^{pmpy}) measures are additive within a sub-category. In the equations below, $s \in k$ means that service *s* is within sub-category *k*.

$$y_{gtk}^{pmpy} = \sum_{s \in k} y_{gts}^{pmpy}$$

$$u_{gtk}^{pmpy} = \sum_{s \in k} u_{gts}^{pmpy}$$

The service-level price measures p_{gts}^{x} are not additive because the sum of all prices is not a conceptually useful definition for the price of a sub-category. Instead, we take the average price of all services within the sub-category, applying a consistent set of weights derived from national data. Using one set of weights for all measures means that cross-geographic variation in the sub-category price comes only from the price of individual services, not from the frequency with which those services were delivered. The sub-category weights ($Swgt_{ts}$) are defined below. Note that there is no *g* subscript because we define one weight for each service in 2018 and 2022 using the national data.

$$Swgt_{ts} = \frac{u_{tks}}{\sum_{s \in k} u_{ts}}$$

The sub-category price measures are then:

$$p_{gtk}^{x} = \sum_{s \in k} (p_{gts}^{x} * Swgt_{ts})$$

2.3 Aggregating sub-category measures into category measures

We aggregated the sub-category measures described in 2.2 to calculate a set of measures at the category-year-geography level. Each observation in this file represents a spending, use, or price measure for a specific category of services in a single geographic area in either 2018 or 2022.

The PMPM spending measure is the sum of the component sub-category spending measures. In the equations below, $k \in c$ means that sub-category k is within service category c.

$$y_{gtc}^{pmpy} = \sum_{k \in c} y_{gtk}^{pmpy}$$

The PMPM use and price measures are weighted sums of the component sub-category measures. The conceptual, clinical, or technical similarity between sub-categories within a category is weaker than between services within a sub-category. For example, the outpatient category includes sub-categories for anesthesia and tests. Anesthesia services are higher cost and higher intensity than a simple blood test and aggregating these two types of care together without a weighting scheme would have lower validity as a measure of category-wide prices and use. We addressed this limitation by developing a set of sub-category weights derived from national data. For the years 2018 and 2022, we calculated the share overall category spending that each sub-category accounted for:

$$Cwgt_{tck} = \frac{y_{tck}}{\sum_{k \in c} y_{tck}}$$

The sub-category use and price measures are then:

$$u_{gtc} = \sum_{k \in c} (u_{gtk} * Cwgt_{tck})$$

$$p_{gtc}^{x} = \sum_{k \in c} (p_{gtk}^{x} * Cwgt_{tck})$$

The PMPM spending measure is, conceptually, the average category PMPM spending by ESI enrollees within the geography in 2018 and 2022 respectively. The sub-category weighting means that the PMPM use measure is no longer average PMPM utilization. It is a weighted average of PMPM utilization at the sub-category level. Similarly, the price measures are the weighted average service price within the category. We convert these values to indices (see Section 2.6) to address differences in the conceptual basis for each measure.

2.4 Service mix measure

In addition to the spending, use, and price measures, we constructed a service mix measure that estimates differences in the types of services delivered within a category. Variation in PMPM spending across geographies could arise from a combination of factors, including:

- Differences in total utilization, even if service mix and prices are identical
- Differences in prices, even if utilization and service mix are identical
- Differences in service mix, even if sub-category-level utilization and prices are identical

To isolate service mix, we construct a modified price measure that uses a weighting scheme that allows for variation across geographies. First, we used the national data (*G*) to estimate the median price of each service across all geographies (*g*) in 2018 and 2022:

$$pmix_{ts} = median\left(pmix_{gts}\right) \ for \ all \ g \ \in G$$

We estimated service-level weights that were specific to each geography. These weights are the share of category use represented by each service. Services that were not delivered in a geography have an implicit weight of zero.

$$Mwgt_{gts} = \frac{u_{gts}}{\sum_k \sum_s u_{gts}} \ for \ s \ \in k \ \in c$$

The sub-category service mix index is the weighted average of the national median service prices within the sub-category. The service mix measure is the average price of a service within the sub-category if service-level prices were fixed at the national median, but service mix is as observed in the geography. Variation in the sub-category service mix index comes only from differences in relative utilization across services, not from differences in prices.

$$Mix_{gtc} = \sum_{s \in C} (pmix_{ts} * \ Mwgt_{gts})$$

2.5 Overall spending and cost burden measures

We summed the PMPM spending measure for each category to measure overall spending within each geography-year combination.

$$y_{gt}^{pmpm} = \sum_{c} y_{gtc}^{pmpm} \; for \; c \in \{IP, OP, PH\}$$

We measured CBSA-level per-capita income using the Personal Income by County, Metro, and Other Areas data from the U.S. Department of Commerce Bureau of Economic Analysis (BEA). The BEA data are measured annually and include per-capita income from wages, proprietor's income, dividends, interest, rents, and government benefits at the CBSA-level. We joined the data for 2018 and 2022 to the HCL analytic file and measured health care cost burden as the share of CBSA-per-capita income that our measured PMPM spending accounted for:

$$CostBurden_{gt} = \frac{y_{gt}^{pmpm}}{pcinc_{gt}}$$

2.6 Converting category measures to indices

The measures reported on the HCL website and analyzed in issue briefs are index measures. We converted the spending, use, price, service mix, and cost burden measures to indices by dividing the measure for each state/CBSA-year unit by the corresponding national-year measure.

For example, the use index for a particular CBSA-year-category is:

$$UseIndex_{gtc} = \frac{u_{gtc}}{u_{national,t,c}}$$

The index values for PMPY spending, use, median price, p25 price, mean price, p75 price, service and mix are all calculated using this approach. We did not construct a category-level cost burden index. Each index theoretically ranges from (0, ∞) where an index value of 1 means that the measure within the geography is the same as the national measure. Subtracting 1 from the index value yields the percent difference between the measure for a particular unit and the national measure. For example, an index of 0.95 means that the measure is 5 percent lower than the national value, and an index of 1.10 means the index is 10 percent higher than the national value.

2.7 Aggregating category indices into overall index measures

We combined the index values for each measure and category into an "Overall" measure. While it is important to measure and evaluate the HCL indices independently by category, providing an overall measure is useful for assessing high-level differences between geographies and understanding how CBSAs and states compare to the national on overall measures of spending, price, use, service mix, and cost burden.

We estimated the overall version of each measure by taking the weighted average of the three corresponding category-level measures. The weights for this calculation are the share of national spending that was attributable to each category in 2022:

$$Owgt_c = \frac{\sum_g y_{gc,2022}}{\sum_c \sum_g y_{gc,2022}} \; for \; g \in G$$

We estimated category weights of 0.224 for inpatient, 0.333 for outpatient, and 0.442 for professional. The overall index is the weighted average of the corresponding category indices:

$$index_{gt} = \sum_c (index_{gtc} * Owgt_c) \; for \; c \in \{IP, OP, PH\}$$

3. Constructing the Inpatient Hospital Market Concentration Index

3.1 Defining a CBSA Hospital Market

Using 2018 and 2022 data from the American Hospital Association (AHA) Annual Survey Database, we constructed a Herfindahl-Hirschman Index (HHI) measure of hospital concentration at the CBSA level. We limited to non-federal short-term general acute care hospitals, inclusive of critical access hospitals, excluding U.S. territories. This measure of hospital concentration is based on fixed hospital geography, and groups hospitals under the same hospital system together within each CBSA. Independent hospitals were counted as their own health system.

These index values are intended to provide descriptive, relative comparisons of the inpatient facility market concentration between the CBSAs within our sample. A high HHI level indicates high market concentration in the area, which typically signifies a lack of local market competition.

3.2 Calculating the Hospital System Level Herfindahl-Hirschman Index

Given our market definition, we computed an HHI measure as the sum of squared hospital system shares of inpatient admissions for individuals from CBSA *g* in year *t*, where g denotes CBSA, *t* denotes year, and *s* denotes health system.

$$Hospital\ HHI_{g,t} = \sum_{s=1}^{S} \left(market\ share_{s,t}^{m}\right)^2$$