Health Care Cost Trends

Calculated Risk: Driving Decisions Using the 5/50 Research

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Abstract

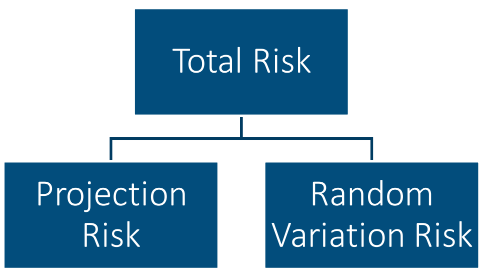
In today's business world, many financial decisions undergo considerable analysis before the decision is made and the decision-maker is often held accountable for the outcomes. The purpose of this research is to introduce the concept of total risk analysis (TRA), which is designed to help the decision-maker answer key questions at the time the decision is made, such as "What are the chances we will lose more than $1 million if we go with this decision?" TRA builds on existing projection techniques and risk models in a manner intended to reflect all possible scenarios. This paper will focus on a specific example of a typical health care decision: setting a budget for claims in the upcoming year. In addition to explaining TRA and providing a case study, this paper presents quantitative research regarding cost distributions for health care costs. These cost distributions provide the information needed to project the random variation risk associated with a projection. These cost distributions are consistent with the "5/50" principle, which says that 50% of all health care costs are associated with 5% of the population. As it turns out, the 5/50 ratio holds for the United States population as a whole, but the concentration percentage, the 50%, varies by population.

Section 1. Introduction to Total Risk Analysis

Back in the day, when computers were slow and data were scarce, risk analysis was often done using a rule of thumb rather than by performing an in-depth analysis. For example, in health insurance it was once common practice to use a 5% provision for adverse deviation (PAD) for any business decision, regardless of the size of the underlying population or the fragility of the underlying data. To compensate for this weakness in the underlying technique, assumptions were often overstated to avoid losing money. As a result, it was seldom clear how much risk an organization was really assuming and how much opportunity was really being lost. Times have changed. Given the ready availability of data and the dynamic nature of business today, this approach is seldom acceptable anymore. Instead, significant business decisions often come under intense scrutiny before the decision is made. Once actual experience is available, the decision-makers are often rewarded or penalized financially based on the results.

The purpose of this research is to provide a practical roadmap for applying total risk analysis (TRA) in the decision-making process as it applies to health care cost projections. TRA can provide a consistent, rational, methodology to answer key questions such as "What are the chances we will lose more than $1 million if we go with this decision?" TRA recognizes both major dimensions of risk associated with a forecast: the projection risk and the random variation risk, as illustrated in Figure 1.1.

Figure 1.1. Total Risk Overview



1.1 THE RATIONALE FOR TRA

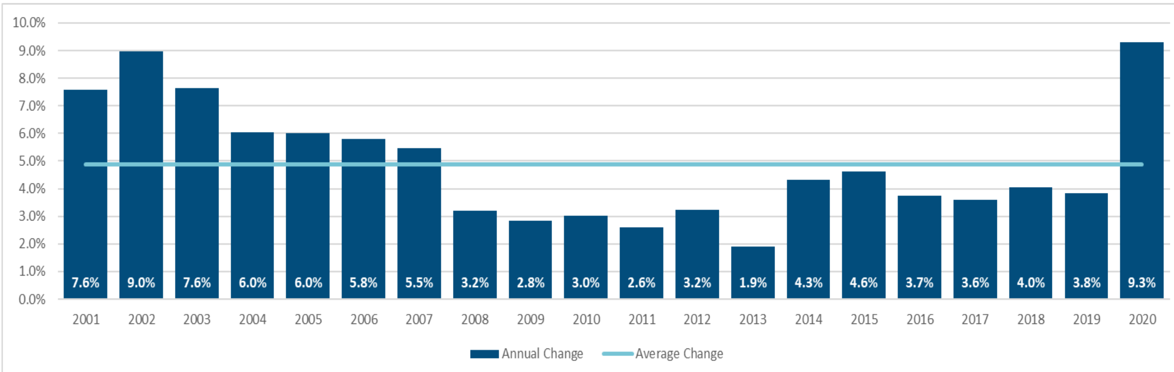
TRA is designed to provide a consistent methodology for accommodating both the difficulty in predicting overall health care costs and the inherent volatility at the member level. A member is a unique individual belonging to a specific health plan, such as an employer group. Both elements are key to determining the total risk associated with a decision or process.

PROJECTION COMPLEXITY

The administration and delivery of health care are complicated, which means the ability to predict the associated costs is often very challenging. In any given year, the costs can increase or decrease greatly because of factors such as the aging of the underlying population, new technologies, renegotiated provider reimbursement contracts and new laws. Because of this complexity, projections cannot rely solely on experience. The projection must also include estimates for one-time changes even though little information may be available on which to base those projections. As a result, it is common to miss a projection by several percentage points. As Figure 1.2 shows, over the 20-year period from 2000 to 2020, the year-over-year increases in the United States per capita health expenditures averaged 4.9% per year, but the minimum increase was only 1.9% and the maximum increase was 9.3%.[1] This volatility in the underlying costs implies that the analyst cannot rely solely on using experience to estimate a future value. In fact, in many cases, little or no experience is available to base the projection on. For example, the rise in costs seen in 2014 was due in part to the implementation of the Affordable Care Act. In 2013, actuaries projecting

2014 premiums did not have any historical basis for key pieces of the puzzle, such as the number of new members joining the risk pool and their health status. Without that information, the chances that the projection would be incorrect are greater than it would be in a more stable environment. Based on one of the authors' experience, the projected trends for 2014 were off by as much as 40% in a few states.

Figure 1.2. Per Capita Trends in National Health Expenditures (2000–2020)



Source: Centers for Medicare and Medicaid Services. 2023. Historical National Health Expenditures, Table 1. *CMS.gov, https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/historical* (accessed Sept. 15, 2023).

To fully understand the risk involved in making a decision, the decision-maker has to be comfortable that all material factors have been taken into account in the projection development. The term "material" in this context is based on the definition of materiality expressed in Actuarial Standards of Practice No. 1, Introductory Actuarial Standard of Practice, Introduction (ASOP 1),[2] which is defined as an error or omission that could impact the decision being made.

VOLATILITY

Health care is also volatile. Many treatments and drugs are very expensive, some costing millions of dollars. The chances that one or more members of a population need a costly treatment is small, but the impact of that treatment can have a material impact on the total costs, especially for smaller payers. The random nature of these incidents often results in a material missed projection.

Measuring volatility is important for two reasons. First, decision-makers need to consider random variation in making the decision at hand to see the complete picture of the total risk. Second, if the actual results are materially different from the projected results, the question is "Was the projection process flawed or was this due to random variation?" If the projection process is determined to be flawed, the next step is improving the process going forward. If the difference is due to volatility, then the next step is to determine if some type of risk transfer, such as stop-loss insurance, is necessary.

1.2 THE CURRENT RISK ANALYSIS LANDSCAPE

Most organizations have some type of enterprise risk management (ERM) system in place to identify, monitor and manage risks. In some cases, the system could be very informal: "My sales are down so I had better figure out why and do something about it." In other cases, the organization may apply ERM using a sophisticated framework such as the one developed by the Casualty Actuarial Society.[3] These frameworks address both qualitative risks, such as the reputation risk, as well as quantitative risks, such as underpricing their products. In the United States, insurers are required to maintain a minimum risk-based capital level to ensure a high probability that they will have enough funds on hand to meet their obligations if actual experience varies significantly from expected. Although risk-based capital provides a measure of security, most organizations want to make day-to-day decisions that obviate the need to tap into that capital. This is where TRA comes in. TRA provides a consistent method of measuring the risk associated with a specific quantitative decision or process.

Currently, the risks associated with the day-to-day decisions are often quantified using projection techniques, such as regression analysis, or risk models, such as the individual risk model and the collective risk model. Both analytical methods provide valuable information to the decision-maker, but each method has its limitations. With some exceptions, neither method alone provides a total picture of the risk associated with a specific decision or process.

Analytical techniques, such as regression analysis or probability analysis, project a key metric, such as the probability of heads on a flip of a fair coin or the expected costs per member per month (PMPM) based on experience for a block of business. From a risk analysis perspective, these two types of projections are very different. A coin flip is a single, definable event. Because it is known in this example that the coin is fair, then the binomial distribution provides all the information necessary to measure the risk associated with betting that the next flip will be heads.

Although a PMPM is a single number, it is not a single, definable event. A coin flip is either heads or tails, with no ambiguity. The cost for a member in a given period is a single, definable event with no ambiguity. A PMPM, however, is the average of a group of members. Because it is an average, the variation around the average needs to be considered in measuring risk. As Table 1.1 shows, a group with 1,000 members can lose $1 million or more if they underprice the expected cost per member per year (PMPY) amount by $1,000 or more. In this example, the analyst's projected claims cost is $5,000 PMPY. Instead, the actual result was $6,000 PMPY for a total loss of $1 million ([$6,000 – $5,000] × 1,000). Regardless of how these numbers are calculated, an assumption is implicit that the distribution of the population, which is shown in Column 1, is the same for both the actual and expected populations. Also note that Column 3 is proportional to Column 2. In fact, each number in Column 3 is 1.2 times the corresponding number in Column 2, where 1.2 = $6,000 ÷ $5,000, the ratio of the total means.

Table 1.1. Projection Risk Example

Bracket	Population Distribution	Expected PMPY	Actual PMPY
	Col. 1.	Col. 2.	Col. 3.
$0	200	$0	$ -
$1 - $5,000	700	$ 1,264	$ 1,517
$5,001 - $10,000	50	$ 7,000	$ 8,400
$10,001 - $100,000	40	$ 32,875	$ 39,450
$100,001 - $1,000,000	9	$ 150,000	$ 180,000
Over $1,000,000	1	$ 1,100,000	$ 1,320,000
Combined	1,000	$ 5,000	$ 6,000

Underpricing is not the only way to lose $1 million in this example. As shown in Table 1.2, if one extra person has a $1 million claim, then the loss will be greater than $1 million. Column 2 in Table 1.2 is identical to column 2 in Table 1.1. The difference between the two results is that in Table 1.2 two people were in the last bracket instead of just one as expected.

Table 1.2. Random Variation Example

Bracket	Population Distribution	Expected PMPY
	Col. 1.	Col. 2.
$0	199	$0
$1 - $5,000	700	$ 1,264
$5,001 - $10,000	50	$ 7,000
$10,001 - $100,000	40	$ 32,875
$100,001 - $1,000,000	9	$ 150,000
Over $1,000,000	2	$ 1,100,000
Combined	1,000	$ 6,100

The risk associated with missing the expected PMPY in this example is the projection risk as shown in Table 1.1. The risk associated with the variance within a PMPY is the random variation (RV) risk as shown in Table 1.2. Historically, the individual and collective risk models have been used to measure the RV risk. Both risk models assume that the mean and distribution associated with the RV risk is known. TRA combines these two concepts by measuring the risk associated with every combination of projection miss and RV risk possible in a consistent manner.

1.3 THEORETICAL BASIS

Conceptually, TRA is similar to the balls in the urn problem taught in most basic statistics courses, where one has a hypothetical urn with some unknown number of black balls and some unknown number of white balls. The student is asked to use a sample to estimate the percentage of black balls in the urn or to test the reasonableness of any prior assumptions about the percentage of black balls in the urn. TRA is similar with several exceptions:

- Instead of a hypothetical urn, one has a very large, “overall” population. In some cases, the overall population will be hypothetical. In other cases, the overall population will be a block of business for a managed care organization (MCO). An MCO is an organization, such as Aetna or Cigna, that insures several lines or business and acts as an administrator for self-insured groups.

- Instead of balls in the urn, each component of the population is a unique member. Each member is “assigned” two numbers: the total costs and member months for that person for the period in question. If a member is continuously enrolled during a calendar year, then the member months associated with that member would be 12. If another member was enrolled for only January and February, then the number of member months associated with that person is two.

- Historical experience data should be considered a sample from the distribution and, as a result, is subject to random variation. For large samples, the variance may be de minimis. For smaller samples, the variance may be material.

- The projected distribution of the hypothetical overall population for a future period is estimated based on results from prior years and expected changes for the upcoming year using standard actuarial techniques.[4] At the time a projection is made, the exact mean of that population is not known, but a range of estimates and the associated probabilities can be determined. This range is the foundation for the projection risk.

- In this report, it will be assumed that for any specific distribution, the cost and member months for any unique member will be determined randomly based on the specified distribution of the underlying population. This is the foundation for the random variation risk.

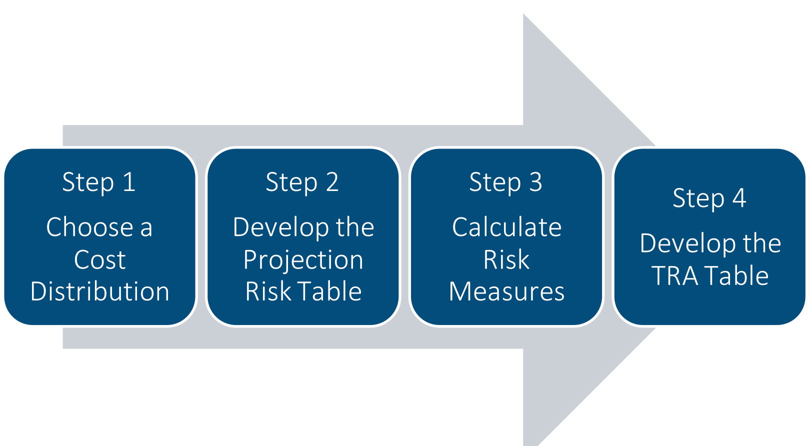
It may seem counterintuitive that the expected cost for a specific member reflects just random variation. As it turns out, the expected cost for a unique member also reflects elements of their risk profile, such as age, geography and health status. Ideally, then, the best way to predict costs would be to divide the population into homogenous groups based on their risk profile. Several potential problems confront this approach, including imperfections in the risk profile process, the shifting nature of the population by risk profile, and the credibility of the data at the risk profile level. In some cases, the analyst may deem these differences material enough to warrant the additional work, and in other cases they may not.

Similarly, it may seem like the experience of an individual should be predictive of future experience. After all, MCOs have been experience rating groups for years. The research underlying this report shows that unique members tend to jump between spending categories between years in a rather consistent way. These jumps are referred to as transition probabilities. Although the authors did not look into this in depth, in all likelihood this is because of the episodic nature of health care, especially for younger populations. Of course, it is possible that a specific group will have lower costs than other similar groups in the population. Various reasons can be identified why one group should consistently have lower costs than other groups, even after accounting for identifiable risk factors, such as age, gender and geography. For example, a member's diet and exercise routine may have a significant impact on one's health care costs. In this report, the assumption will be that differences by groups will be due to random variation unless proven otherwise. Techniques for determining such differences are outside the scope of this report.

1.4 HOW TRA WORKS

Like any analytical process, the application of TRA depends on the objective of the analysis, the data available, and the time and resources available to conduct the analysis. In this report, the authors present one example of how to perform TRA. This example follows the four-step process illustrated in Figure 1.3.

Figure 1.3. The TRA Process



COST DISTRIBUTION

As noted above, the RV risk is based on the member months and claims from a large population. This information can be summarized and used in calculations using a claims probability table (CPT), also known as a continuance table. CPTs have been around for years and are most often used for calculating cost-share features such as deductibles, coinsurance and out-of-pocket maximums. The values in a CPT will change each year in response to inflation, new clinical techniques and other factors. As shown in Section 2, however, the shape of the tables tends to remain consistent year over year. The shape is referred to as a cost distribution. Once the cost distribution is chosen, then the CPT for any assumed or actual value can be determined by performing the appropriate calculations using the cost distribution, as illustrated in Figure 1.4.

From a mathematical perspective, a cost distribution can be thought of as a type of probability distribution function just like the binomial distribution is a type of probability distribution function. Parameters are required to convert a distribution type to an actual probability distribution, which can then be used to calculate probabilities. In the binomial distribution, the parameter is the probability of success, usually denoted as p. Once the value of p is known or assumed, then the probability of success and the probability of failure can be determined. In TRA the average cost, that is, the mean of the distribution, is the necessary parameter. Once that number is known or assumed, then a CPT can be derived from the cost distribution and probabilities can be calculated from the CPT. Examples are given in Section 2.

THE PROJECTION RISK DISTRIBUTION

The key metric is the measure used to define risk in a specific situation. This report will focus on the expected PMPM as the key metric, but the key metric could just as easily be a loss ratio, a sales target or any other item relevant to the decision at hand.

Needless to say, the actual value of the key metric is unlikely to be exactly what is projected. The projection risk probability distribution assigns a probability to all possible outcomes. If the key metric is estimated using regression analysis, then the variance of the probability distribution can be estimated using the standard error. Some elements of the projection, however, cannot be projected using experience. For example, to measure the projected impact of a new drug on future costs, the analyst must at a minimum consider the target population for the drug, the percentage of those in the target population likely to take it, the expected costs, and, if it has not yet been approved by the U.S. Food and Drug Administration, the approval date. Although techniques for estimating the expected cost and the associated probability distribution are outside the scope of this paper, the techniques will depend to some degree on professional judgment.

RISK MEASURES

Each decision-maker will have one or more measures of risk they want to consider during the process. For TRA to work, those risk measures have to be quantifiable. Examples of risk measures include the expected profit or loss and the probability of losing more than $1 million. Cost distributions and the CPTs derived from the cost distribution measure the risk associated with an individual. Risk is seldom measured at the individual level, however. Instead, risk is measured at a group level, such as a specific employer group or the group insurance business for an MCO. As noted in Section 1.3, this means that the experience for a group can be treated as a sample from the overall population. This means that it is reasonable to assume that the Central Limit Theorem applies, so the RV risk associated with any candidate value of the key metric can be measured using the normal distribution with a mean equal to the candidate key value and with a variance based on the coefficient of variation from the cost distribution and the average members in the group.

TRA TABLE

Once the information above is available, the total risk can be determined as the weighted average of the risk factors, where the weights are based on the projection risk distribution described above, as shown in Equation 1.1.

Equation 1.1. Total Risk

Total Risk = $\int_{-\infty}^{+\infty} e(x)p(x)dx = \int_{0}^{1} e(y)dF(y)$,

where:

- x is the value of the key metric.
- y is the inverse of x ($x = F^{-1}(y)$, where $F(\cdot)$ is the cumulative probability distribution for the key metric.
- $e(x)$ is the error measure for the key metric with value x.
- $p(x)$ is the probability of x.

In the integral on the left, this equation indicates that the total risk is the weighted average of the risk measure over all possible values of the key metric. Since this method is straightforward and easy to explain, it is the preferred method when there is only one component of the key metric projection. In health insurance, the projection almost always consists of several components, including cost and utilization. Each component has its own unique variance formula. In that case, it is easier to sum over all possible probability values. The results should be equivalent.

Although integrals are the most theoretically correct methodology, two practical reasons exist to approximate the result using histograms. First, the result associated with an integral is a single number, a black box of sorts. One way to display the results is by scenario. Under this approach, the results can be displayed in a manner that allows the decision-maker to "kick the tires" regarding the underlying methodology and to understand the impact of key assumptions. The second reason is that it is often easier to perform the calculations using a spreadsheet.

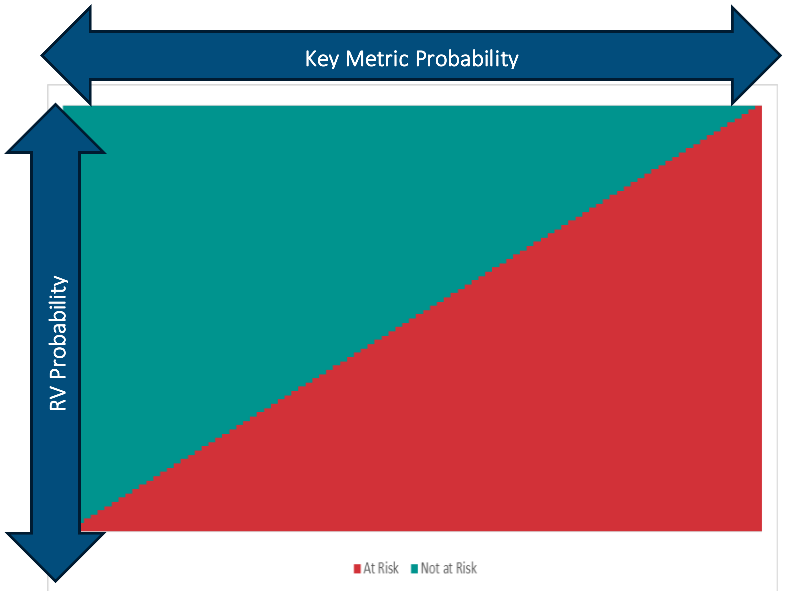
1.5 TRA LIMITATIONS

The British statistician George Box famously said, "All models are wrong, but some are useful."[5] TRA is no exception. According to Actuarial Standard of Practice No. 56, Modeling Standard of Practice (ASOP 56),[6] every U.S. actuary is required to disclose flaws in model design that could materially impact the results. In applying ASOP 56 to a specific analysis, some underlying limitations of TRA need to be considered.

DOUBLE COUNTING AND UNDERCOUNTING

In the case study described in this paper we see virtually no structural risk of double counting or undercounting. As shown in Figure 1.4, TRA calculates risk based on two dimensions. The first dimension is the key metric value. Every value of the key metric is accounted for once and only once in the projection risk distribution table. For any given value of the key metric, however, a chance exists that a specific group will be at risk simply because of random variation. For example, the group may have materially more high-cost claimants than other groups, which will put them at risk even if the average for the overall population is correct. As Figure 1.4 shows, the higher the key metric, the more likely the group is of being at risk for missing the projection because of random variation. That said, every group is at some level of risk because of random variation. A bright line lies between being at risk and not being at risk. That line, which is represented by the diagonal in the figure, varies by the risk metric under consideration.

Figure 1.4. TRA Dimensions



The reason for no double counting or undercounting in this report is because the RV risk is based on the cost distributions. Cost distributions are derived independently from the key metrics and are remarkedly stable over time. The shape of the curves remain the same, however. In developing other applications of TRA, we might find a risk of double counting and/or undercounting the total risk if some construct similar to cost distributions is not available.

QUALITATIVE ANALYSIS

By its very nature, TRA is a quantitative exercise. That means that many qualitative elements of risk, such as the reputation risk, cannot be incorporated into the results unless the analyst is willing to assign values to it. That rarely happens. One qualitative element of risk is crucial to TRA, however: the model risk. Model risk includes the incorrect design of the model, inappropriate use of data, and any other flaws that may make a material difference in the model output. According to ASOP 56, the remedy for design risk is to correct the error, make appropriate adjustments or disclose the risk to intended users.

SIMPLICITY VERSUS COMPLETENESS

Ideally, TRA completely accounts for all quantifiable sources of risk. That may mean that the process may become unwieldy. One of the challenges an analyst faces is finding the right balance between simplicity and completeness. As always, key factors in deciding how to proceed include materiality, resources available and the ability to communicate with the decision-maker. In this report, the authors make three key simplifying assumptions that could be material in some analyses. As always, it is up to the actuary to determine materiality for any given analysis.

Normal Distribution

Cost distributions form the basis for the probability distribution function of a member. Risk is seldom measured at the individual level. It is usually measured at the population level. Specifically, as discussed in Section 1.3, the experience for a specific group is considered a sample of the overall population. According to the Central Limit Theorem, the distribution of all samples is normal, regardless of the underlying probability distribution, the cost distribution or the corresponding CPT in this report. The mean of the distribution is μ, the population mean, and the variance is $\sigma^2 \div N$, where σ^2 is the population variance. In this report, the authors have assumed that the Central Limit Theorem applies in full. In real life, the distribution may be skewed, especially if the value of N is small. Similarly, the authors have assumed that the standard error for a regression analysis is normal, when, in fact, it may be a Student's t distribution, or it may be skewed.

Independent Variables

In Section 3, the authors assume that all variables used in the case study projection are independent of one another, which may not always be the case.

Average Members

In this report, the analysis in Section 3 is based on average members instead of unique members, in keeping with standard practices throughout the industry. In most cases, this will not have a material impact. After all, average members = unique members × the average duration. Assuming that the average duration is a constant over all brackets, little or no impact should be seen on the calculations of the standard deviation. The problem is that duration is not constant by spending bracket, so this could have a material impact on some analyses, especially those involving high-cost claimants.

VALIDATION OF ASSUMPTIONS

The authors did not validate the assumption that the experience of a group behaves like a random sample. That said, the authors have tested the concepts using proprietary employer data before and found that the assumption holds or at least holds enough to be useful. The specific techniques used to validate the assumptions using this data include the following:

- *Group Distribution*. After adjusting for known differences in risk profile, such as the age-gender of the population, the PMPMs by group form a bell-shaped curve similar to the normal curve. The variance for this curve will differ from the variance predicted using the cost distribution because the adjustment for risk profile adds another layer of projection risk.
- *Trend Impact*. Based on TRA theory, one has a 50/50 chance that any group will "beat trend" on an allowed basis after adjustment for changes in risk profile and other group-specific differences. Of course, the variance will vary by group size.

1.6 ABOUT THE REPORT

This report is designed to be a practical guide rather than a theoretical paper, and so the general approach is to describe the applicable principles, illustrate how to apply the principles, and discuss possible pitfalls. The discussion will focus on how to test to ensure that the applicable principles apply given the circumstances at hand. Although no theorems or proofs are offered in this paper, the authors look forward to reading more theoretical papers.

The key sections of the report include the following:

- *Section 2. Research Results*. This section describes the process of building cost distributions and presents the related research results. This section corresponds to the first step in Figure 1.3.
- *Section 3. Case Study*. This section builds off Section 2 by providing a case study example using the remaining steps described in Section 1.4. A companion Excel file contains more detailed information underlying the research.

- *Section 4. Areas for Further Research*. The concept of TRA should be applicable in any situation involving a projection as long as a construct is similar to a cost distribution. Some health care examples include group and individual insured business, value-based reimbursement, and resource management. These techniques can also be used for long-term products such as life, annuities and long-term care.

Section 2: Research Results

As noted in Section 1, the first step in applying TRA is to choose a cost distribution for use in determining the RV risk. The purpose of this section is to present the process for building a cost distribution and to describe considerations for choosing a cost distribution. This section also presents the results of the research portion of this project. The key findings in this section are the following:

- *The 5/50 Principle*. The 5/50 principle is similar to the Pareto principle in that spend is concentrated in a relatively small percentage of the population. Several published studies have shown that for the overall population about 50% of U.S. health care spend can be attributed to roughly 5% of the population.[7] This study shows that the 5/50 principle applies, but the concentration percentages vary by population. In 2017 the top 5% accounted for 63% of the spend for the Commercial population and 43% for the Medicare Advantage population.

- *Consistency*. The cost distributions, transition probabilities and source distributions for a specific population were consistent year over year during the study period. That said, the data may not be as consistent in the future because of changes in reimbursement methodologies, treatment patterns and the COVID-19 pandemic.

- *Coefficient of Variation*. The coefficient of variation, which is defined as the standard deviation divided by the mean, is relatively stable for both the commercial and Medicare populations. The coefficient of variation is a key element in determining the RV risk.

- *Leveraging*. Health care costs increase every year, so the percentage of costs above or below a specified dollar amount changes every year. This concept is referred to as leveraging or the iceberg effect.

2.1 HISTORICAL COST DISTRIBUTIONS

As noted in Section 1, cost distributions and the claims probability tables (CPTs) derived from cost distributions are required for estimating the RV risk. Actuaries have been using CPTs, also known as claims continuance tables, for years to calculate the actuarial value of cost-sharing features such as deductibles and coinsurance. A CPT is simply a summary of the balls in the urn described in Section 1.3. A cost distribution can be derived from a CPT by grouping members based on the percentage of total costs. Conversely, a continuance table can be derived from a cost distribution if the mean is known.

THE DATA

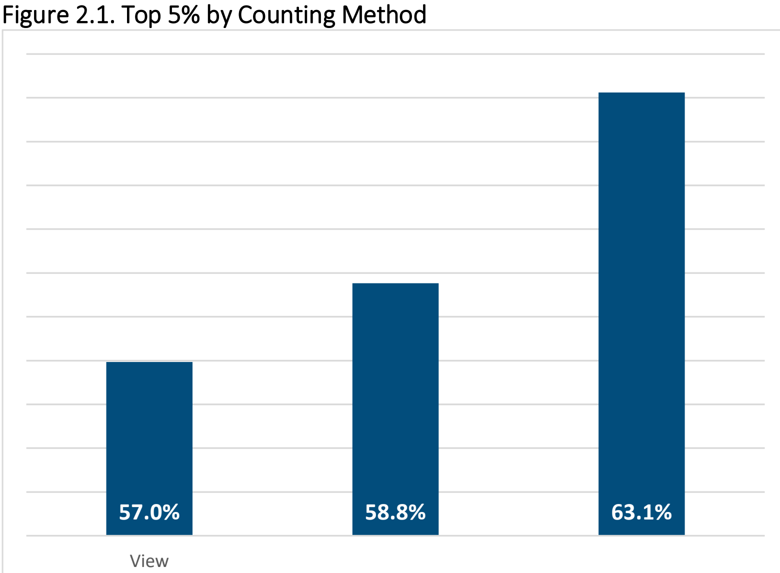
The data used to develop the cost distributions in this report were sourced from the Health Care Cost Institute (HCCI) database for incurred years 2013–2017. This database is a longitudinal, multipayer data set, which includes both pharmacy and medical claims.[8] The data included an average of 48 million members for the commercial population. This represents approximately 30% of the total commercial population,[9] which includes large group, small group and individual coverages. The data also include an average of 6.4 million members for the Medicare Advantage population, or approximately 33% of the Medicare population in 2017.[10]

As discussed in Section 1.3, development of a CPT or a cost distribution from historical data for a specific population and period requires three data elements:

- *A Unique Member ID.* A unique member identification number is assigned to each member when they join the health plan. That information is carried through all data collected about the member as long as the member stays in the health plan.
- *Member Months.* Member months represent how many months a unique member is covered during a period. If a member is continuously enrolled in a health plan for an entire calendar year, then the number of member months associated with that member would be 12. Similarly, if a person was covered only for February, March and April, the number of member months associated with that member would be 3.
- *Allowed Amount.* Although relatively vague terms such as "costs" and "spend" are often used in general conversations about health care, precise definitions are required when performing an analysis. For the purposes of this paper, the authors use the "allowed amount" to define costs. The allowed amount represents the total paid to a provider, including the amount paid by the payer, the net paid, and the amount paid by the member in the form of cost share, where cost share includes deductibles, coinsurance and copays.

All covered individuals were included in the data pull, including new entrants during the year, terminations during the year and continuously enrolled during the year. This view is consistent with how health plans analyze their data for financial and pricing purposes. Some published papers, however, were designed for different purposes, so that research was based on other views. For example, the HCCI published a report analyzing costs for top spenders based on members continuously enrolled for a two-year period.[11] This view of the data provides a better view of what happens at the member level than the health plan view. The underlying 5/50 principle, however, applies to both views of the data. The primary difference is the percentage of total cost attributable to the top 5% of spenders, as illustrated in Figure 2.1.

Figure 2.1. Top 5% by Counting Method



THE DEVELOPMENT PROCESS

In this paper, the cost distributions were developed using historical data. For example, a cost distribution can be derived directly from raw data by starting with a CPT as illustrated in Table 2.1. A more detailed version of this calculation can be found in Section 2 of Tabs 2–11 of the companion Excel file. The columns are derived as follows:

- Columns 1, 2 and 3 are summaries from the data pull.
- Column 4 = Column 2 ÷ 12.
- Column 5 = Column 3 ÷ Column 4.

Table 2.1. Claims Probability Table Example

Bracket	Unique Members Col. 1	Member Months Col. 2	Total Allowed Col. 3	Average Members Col. 4	PMPY Col. 5
$0 - $10,000	23,445,610	200,179,902	$ 2,420,149,001	16,681,659	$ 145
$10,000 - $87,000	11,723,337	124,525,972	$ 12,661,908,403	10,377,164	$ 1,220
$87,000 - $300,000	7,102,301	77,037,381	$ 27,864,318,536	6,419,782	$ 4,340
$300,000 - $370,000	2,355,607	25,976,584	$ 24,470,028,924	2,164,715	$ 11,304
$370,000 and Above	2,434,464	27,033,569	$ 116,390,059,753	2,252,797	$ 51,665
Combined	47,061,319	454,753,408	$ 183,806,464,617	37,896,117	$ 4,850

A cost distribution development is a straightforward calculation using columns 1, 2 and 3 in Table 2.1, as shown in Table 2.2. Although the structure of a cost distribution may vary, the minimum required information includes columns 3 (member months by bracket, which serves as weights) and 5 (allowed by bracket).

Table 2.2. Cost Distribution Example

Bracket	Unique Members by Bracket Col. 1	Cumulative Unique Members Col. 2	Member Months by Bracket Col 3	Cumulative Member Months Col. 4	Allowed by Bracket Col. 5	Cumulative Allowed Col. 6
Bottom 50%	50%	50%	44%	44%	1%	1%
Top 25% to 50%	25%	75%	27%	71%	7%	8%
Top 10% to 25%	15%	90%	17%	88%	15%	23%
Top 5% to 10%	5%	95%	6%	94%	13%	37%
Top 5%	5%	100%	6%	100%	63%	100%
Combined	100%	100%	100%	100%	100%	100%

The cost distribution can be used to develop a claims probability table using techniques similar to those shown in Table 2.3. In Table 2.3 the weights shown in Column 1 correspond to Column 3 in Table 2.2, and the allowed Distribution shown in Column 2 corresponds to Column 5 in Table 2.2. The project PMPY shown in Column 3 of Table 2.3 can be calculated as Projected PMPY = (Target PMPY × Allowed Distribution) ÷ Weight). For the bottom 50% bracket this translates to $179 = ($6,000 × 1%) ÷ 44%. A PMPY can be converted to a PMPM by dividing it by 12.

Table 2.3. Claims Probability Table (Candidate per Member per Year (PMPY) = $6,000)

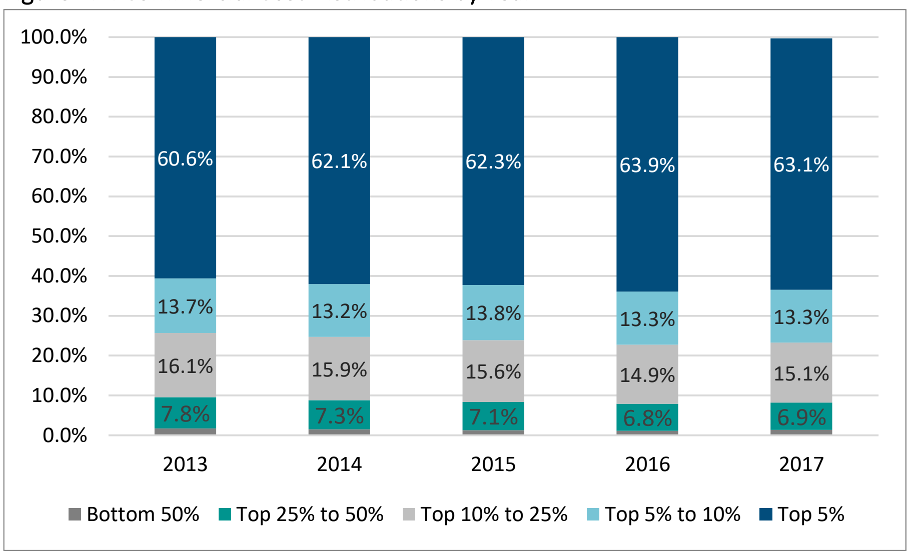
Bracket	Weights Col. 1	Allowed Distribution Col. 2	PMPY Projected Col 3
Bottom 50%	44%	1%	$ 179
Top 25% to 50%	27%	7%	$ 1,509
Top 10% to 25%	17%	15%	$ 5,369
Top 5% to 10%	6%	13%	$ 13,984
Top 5%	6%	63%	$ 63,911
Combined	100%	100%	$ 6,000

This approach requires considerable data, especially in situations where an accurate representation of the top spenders is important. One alternative is to simply use an existing cost distribution such as the ones shown in the companion file. In some cases this will be a practical and appropriate course of action. In other cases, it may not be the best course of action. If some data are available, it may be prudent to do a chi-square test to determine if the overall distribution is reasonably close to the data.

CONSISTENCY OF RESULTS

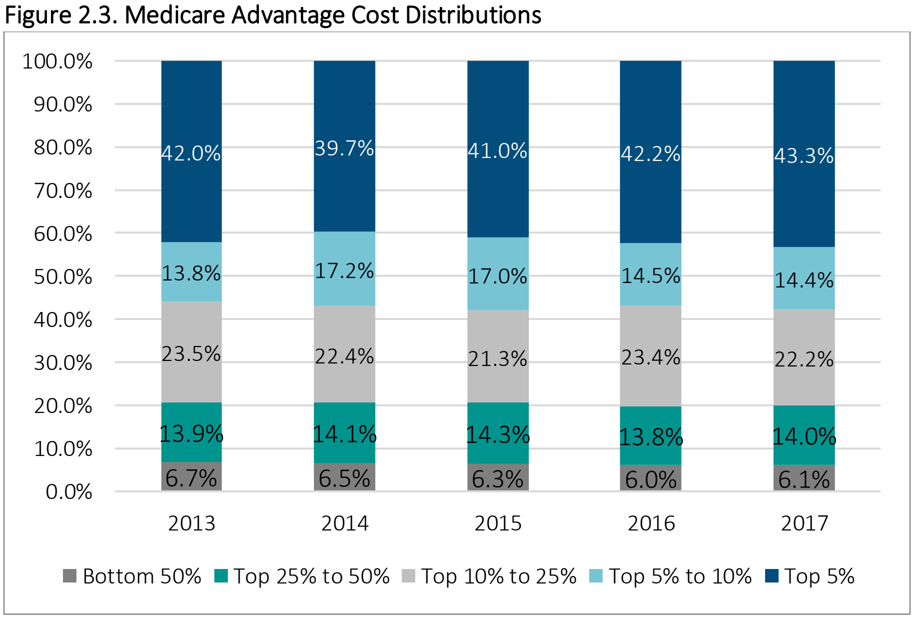
Historically, cost distributions have been consistent over time, as shown in Figure 2.2. These cost distributions follow the 5/50 principle because the spend is concentrated in the top 5% of spenders. This consistency implies that the cost distributions are stable and reliable for use in the RV calculations.

Figure 2.2. Commercial Cost Distributions by Year



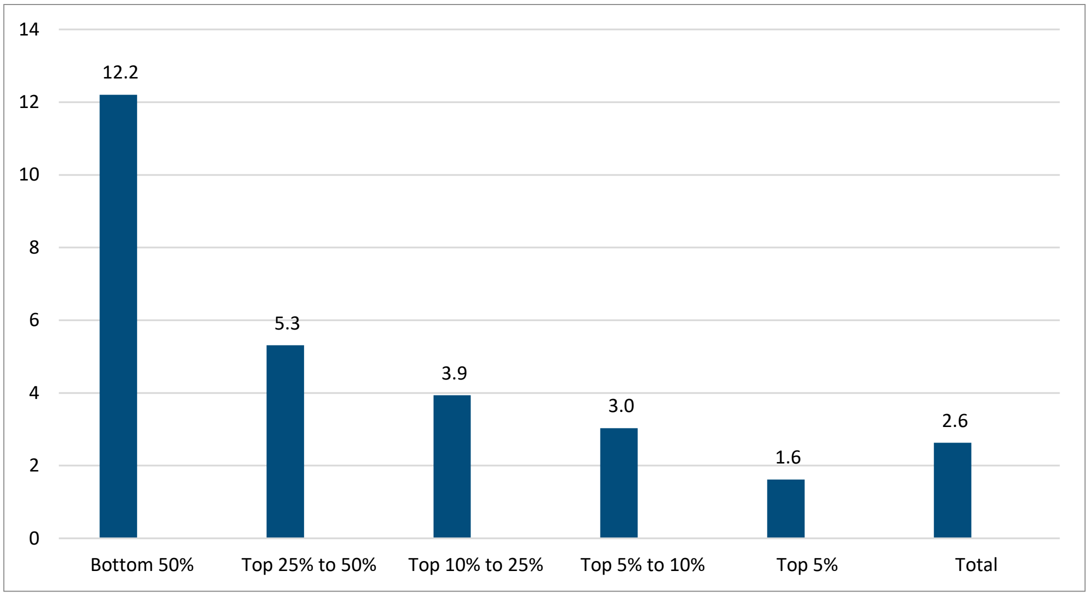
As Figure 2.3 shows, the cost distributions for Medicare Advantage are also very consistent over the study period, but the cost distributions are very different from the Commercial cost distributions.

Figure 2.3. Medicare Advantage Cost Distributions



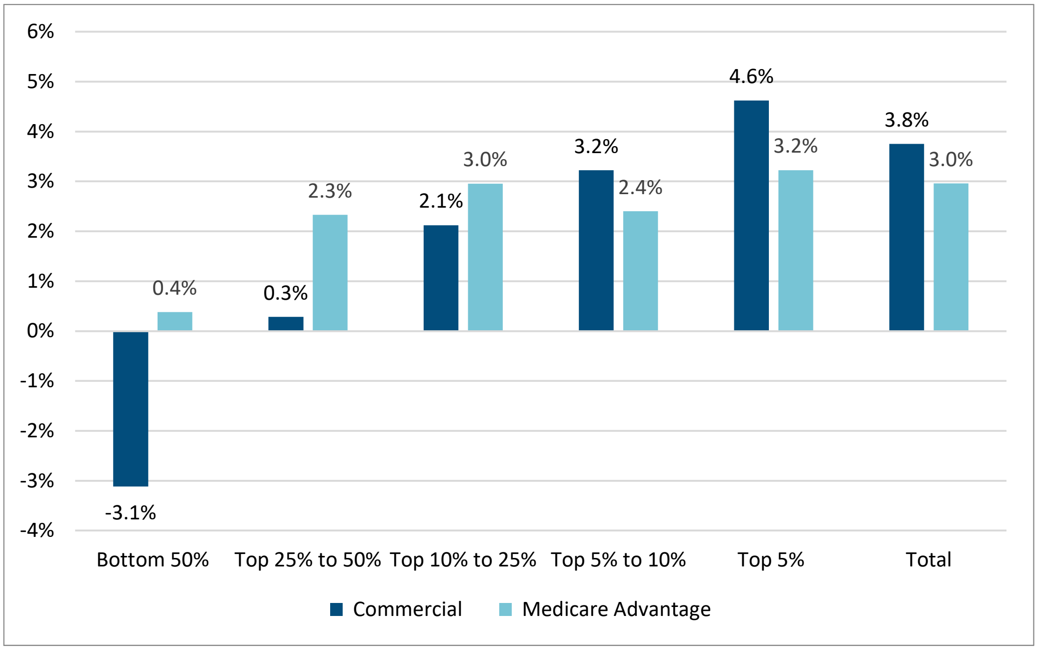
This may seem counterintuitive at first, because it has been well documented that costs tend to increase as a person ages.[12] The data from this project support that. In fact, as shown in Figure 2.4 in 2017 the average Medicare Advantage PMPM is 2.6 times the average Commercial PMPM. The difference in the distribution is that Medicare Advantage members in the lower spender categories have higher relative costs than the members in the top 5%. Although the authors did not verify this, in all likelihood this difference is probably due to the fact that older people tend to have more chronic diseases, which means more maintenance drugs, office visits and tests.

Figure 2.4. 2017 Ratio of Medicare Advantage PMPM to Commercial PMPM by Spending Category



Although the results show relative consistency year over year, this consistency cannot be taken for granted. In any given year, because changes in treatment patterns and reimbursement methodologies can impact a cost distribution. For example, as illustrated in Figure 2.5, the average cost per unique member has increased more for the top 5% than for other categories for both the Commercial and Medicare Advantage populations. In addition, it is highly likely that the COVID-19 pandemic may have served as a disruptor for cost distributions due to factors such as the rise in telemedicine and the long-term impact of the disease.

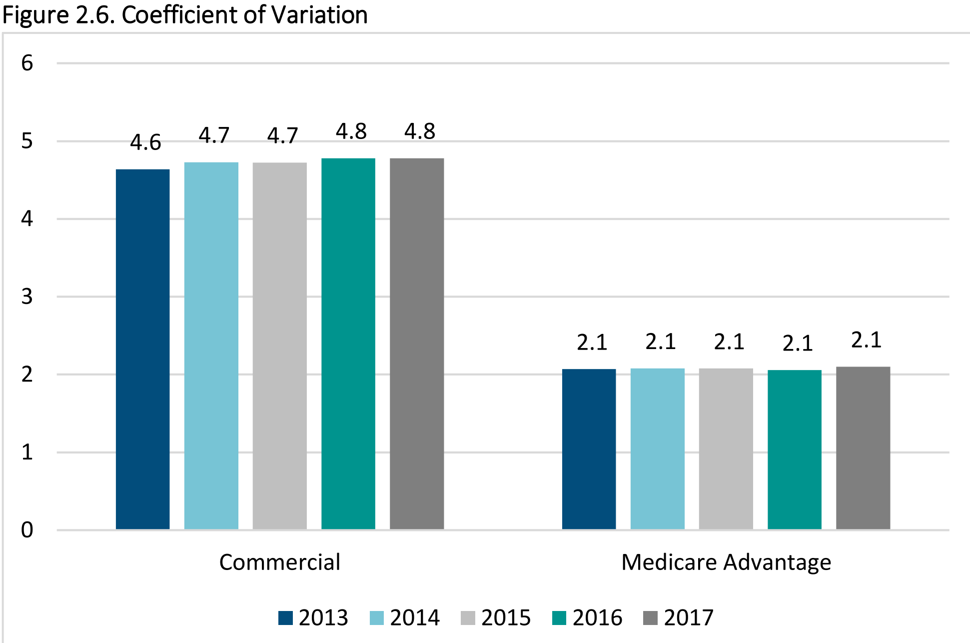
Figure 2.5. Average Cost Increases per Unique Member (2013–2017)



THE COEFFICIENT OF VARIATION

Not surprisingly, the coefficient of variation (the standard deviation divided by the mean) for both Commercial and Medicare Advantage is relatively high, as shown in Figure 2.6. The formulas underlying these calculations are based on standard statistical formulas,[13] treating the data shown in the companion file as a sample of the overall insured population with one exception: the calculations were based on average members, not unique members. This could have a material effect on the results depending on the analytics.

Figure 2.6. Coefficient of Variation



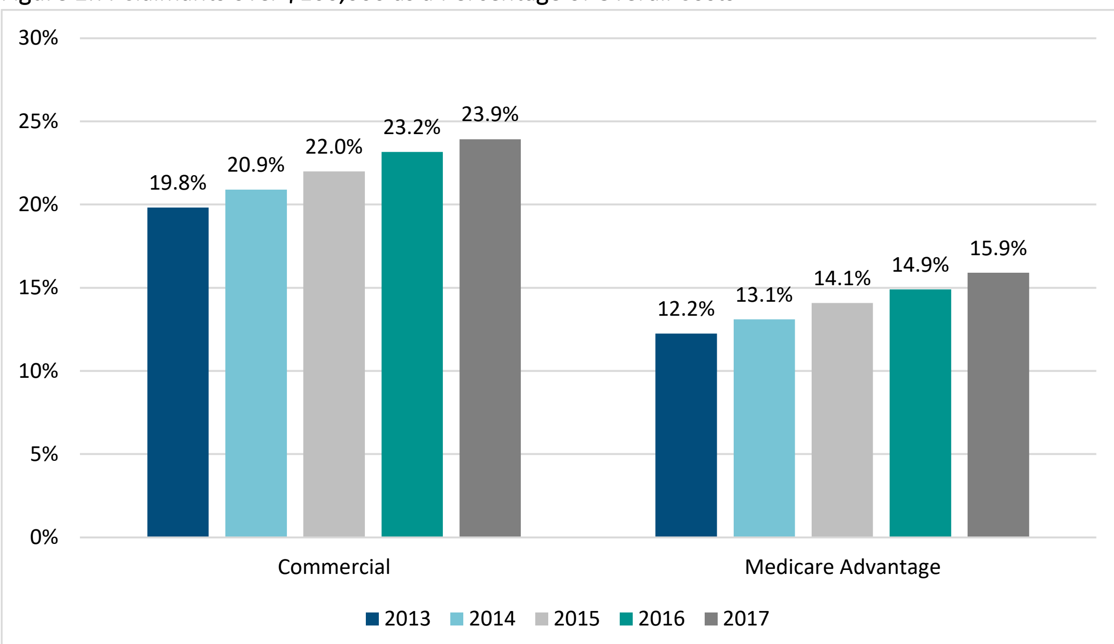
LEVERAGING EFFECT

Historically, variance has often been described in terms of unique members exceeding a specified dollar amount during a year. The specified amount is often referred to as a trigger. The unique members are referred to as high-cost claimants, large claims or shock claims. High-cost claimants have always played an important role in analyzing health care costs for the following reasons:

- High-cost claimants are relatively easy to identify and to explain.
- High-cost claimants correspond to risk transfer techniques such as specific stop loss.
- Depending on the trigger, most of the variance can be attributed to high-cost claimants.

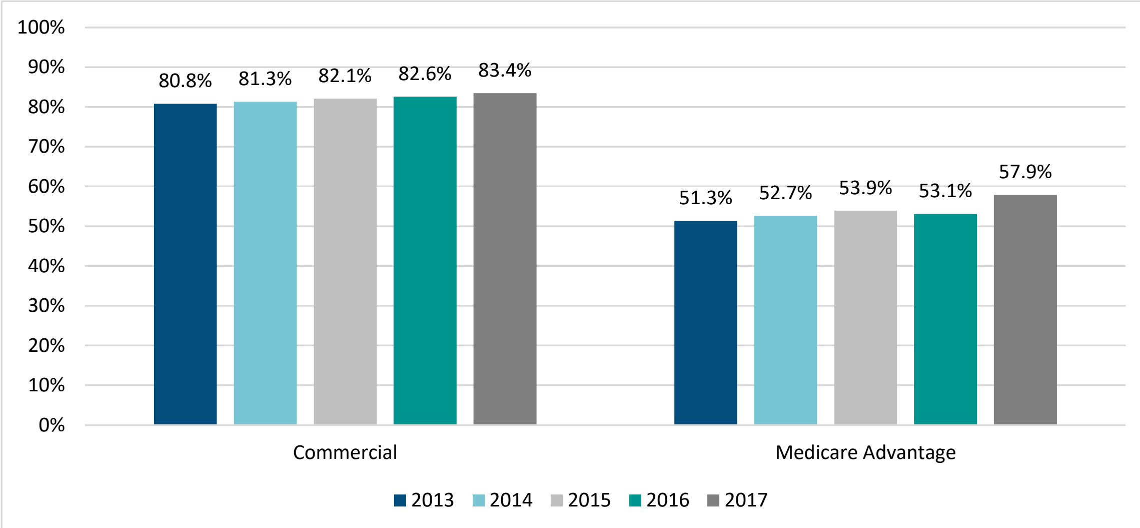
The overall cost of health care increases over time as shown in Figure 1.1, and so the impact of high-cost claimants also will increase over time, as shown in Figure 2.7. Intuitively this makes sense given the stability of cost distributions: The higher the overall costs, the more members reach the trigger point. This is known as the leveraging effect.

Figure 2.7. Claimants over $100,000 as a Percentage of Overall Costs



Similarly, as shown in Figure 2.8, the variance associated with high-cost claimants increases slightly over time. in this report, variance will be described in terms of the total sum of squares of error, as described in standard statistic textbooks[14] and illustrated in Section 6 of the cost distribution tabs in the companion file.

Figure 2.8. Claimants over $100,000 as a Percentage of Total Variance



2.2 TRANSITION PROBABILITIES AND SOURCE DISTRIBUTIONS

The population underlying a cost distribution changes every year. Some members join the population during the year. Some leave the population. Some members get sicker during the year. Some get better. Everyone ages a year. Transition probabilities describe these shifts in the population. Source distributions describe the end result of the population shifts in terms of the source of the population on a spender group by spender group basis.

Transition probabilities and source distributions are important for two reasons. First, both concepts support the assumption that the experience of a group is a random sample from the larger population. It is not proof of that, but it is consistent with the theory and an area for further exploration. Second, transition probabilities and source distributions may provide a valuable methodology for measuring the impact of care management techniques on the total cost of care. Although that methodology is outside the scope of this paper, it is discussed briefly in Section 4.

A LITTLE POPULATION THEORY

To project the aging of a population, a demographer would at a minimum consider the following:

- The age distribution of the current population.
- Expected birth rates.
- Mortality rates by age.
- The aging of the remaining population (everyone in the population ages by one year).

The aging of an insured population can be estimated in a similar way, but with a few twists:

- Instead of birth rates, the age distribution of the new entrants, which includes members new to the group and those opting in for coverage during the year.
- The age distribution of the terminations, which includes those leaving the group and those opting out of coverage.
- The aging of the continuously enrolled population (everyone ages by one year).

TRANSITION PROBABILITIES

Table 2.4 shows the raw 2016 distribution of unique members by their status in 2017. Of the total 50,696,067 members in 2016, 16,926,654 or 33.4% left the population in 2017. These members are labeled terminations.

Table 2.4. 2016 Commercial Members by 2017 Status

	Status in 2017						
Status in 2016	Top 5%	Top 5-10%	Top 10-25%	Top 25-50%	Bottom 50%	Terminated	Total
Top 5%	643,260	277,785	403,658	321,775	231,452	656,873	2,534,803
Top 5-10%	281,933	353,672	557,967	421,037	292,225	627,986	2,534,820
Top 10-25%	424,784	555,518	1,842,017	1,810,134	1,064,497	1,907,448	7,604,398
Top 25-50%	324,182	423,115	1,660,187	3,722,241	3,102,271	3,442,022	12,674,018
Bottom 50%	253,331	295,134	1,125,554	2,954,374	10,427,310	10,292,325	25,348,028
Total	1,927,490	1,905,224	5,589,383	9,229,561	15,117,755	16,926,654	50,696,067

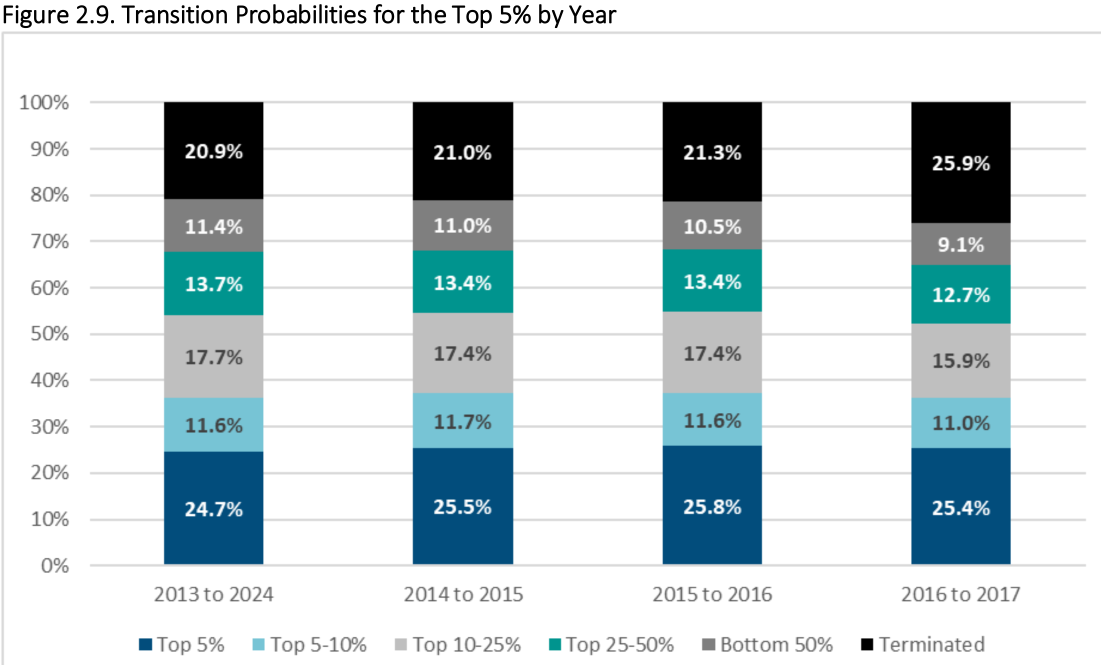
As Table 2.5 shows, transition probabilities can be calculated using row-wise distributions. For example, the 25.4% of the top 5% that stayed in the top 5%, shown in the upper left-hand corner, is calculated as 643,260 ÷ 2,534,803, where 2,534,803 is the total for the first row. The terminations are members who left the health plan before the beginning of the 2017 plan year.

Table 2.5. 2016 Commercial Transition Probabilities

	Status in 2017						
Status in 2016	Top 5%	Top 5-10%	Top 10-25%	Top 25-50%	Bottom 50%	Terminated	Total
Top 5%	25.4%	11.0%	15.9%	12.7%	9.1%	25.9%	100.0%
Top 5-10%	11.1%	14.0%	22.0%	16.6%	11.5%	24.8%	100.0%
Top 10-25%	5.6%	7.3%	24.2%	23.8%	14.0%	25.1%	100.0%
Top 25-50%	2.6%	3.3%	13.1%	29.4%	24.5%	27.2%	100.0%
Bottom 50%	1.0%	1.2%	4.4%	11.7%	41.1%	40.6%	100.0%
Total	3.8%	3.8%	11.0%	18.2%	29.8%	33.4%	100.0%

Transition probabilities also tend to be consistent year over year, as shown in Figure 2.9.

Figure 2.9. Transition Probabilities for the Top 5% by Year



SOURCE DISTRIBUTIONS

The source distributions for 2017 include both those continuously enrolled in both 2016 and 2017 and the 13,291,996 new entrants who were not in the population in 2016, as shown in Table 2.6.

Table 2.6. 2017 Commercial Members by 2016 Status

	Status in 2017					
Status in 2016	**Top 5%**	**Top 5-10%**	**Top 10-25%**	**Top 25-50%**	**Bottom 50%**	**Total**
Top 5%	643,260	277,785	403,658	321,775	231,452	1,877,930
Top 5-10%	281,933	353,672	557,967	421,037	292,225	1,906,834
Top 10-25%	424,784	555,518	1,842,017	1,810,134	1,064,497	5,696,950
Top 25-50%	324,182	423,115	1,660,187	3,722,241	3,102,271	9,231,996
Bottom 50%	253,331	295,134	1,125,554	2,954,374	10,427,310	15,055,703
New Entrants	425,581	447,849	1,469,834	2,535,774	8,412,958	13,291,996
Total	2,353,071	2,353,073	7,059,217	11,765,335	23,530,713	47,061,409

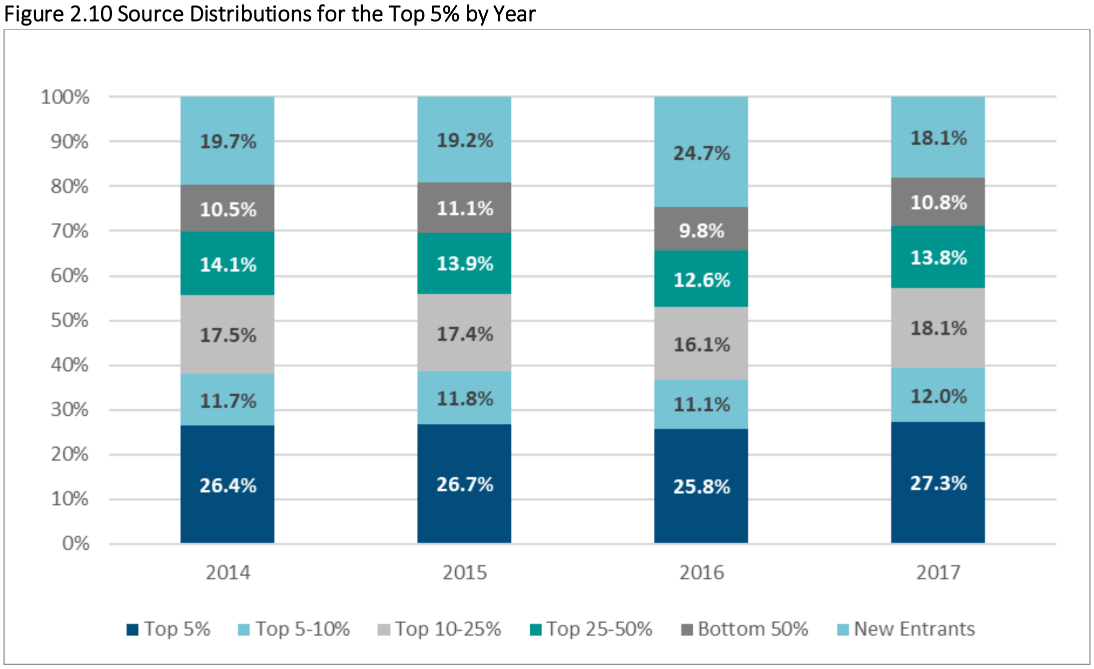
The 2017 source distributions then can be calculated by taking columnwise distributions, as shown in Table 2.7. For example, the 27.3% of the 2017 spender category who were also in the top 5% in 2016 can be calculated as 643,260 ÷ 2,353,071, where 2,353,071 is the total in the first column.

Table 2.7. 2017 Commercial Source Distributions

	Status in 2017					
Status in 2016	**Top 5%**	**Top 5-10%**	**Top 10-25%**	**Top 25-50%**	**Bottom 50%**	**Total**
Top 5%	27.3%	11.8%	5.7%	2.7%	1.0%	4.0%
Top 5-10%	12.0%	15.0%	7.9%	3.6%	1.2%	4.1%
Top 10-25%	18.1%	23.6%	26.1%	15.4%	4.5%	12.1%
Top 25-50%	13.8%	18.0%	23.5%	31.6%	13.2%	19.6%
Bottom 50%	10.8%	12.5%	15.9%	25.1%	44.3%	32.0%
New Entrants	18.1%	19.0%	20.8%	21.6%	35.8%	28.2%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source distributions are also consistent over time as shown in Figure 2.10.

Figure 2.10 Source Distributions for the Top 5% by Year



2.3 THE COMPANION FILE

Detailed data relating to key findings are summarized in the companion Excel file. This file also includes several examples of calculations discussed below. The data produced as part of this research include the following:

- *Cost Distributions*. A cost distribution simply groups a population by their percent of total spend. A total of 10 cost distributions were produced and summarized in the companion file: one for each year in the study period (2013–2017) for the Commercial population (Tabs 2–6) and one for each year in the study period for the Medicare Advantage population (Tabs 7–11).

- *Transition Probabilities*. A transition probability measures the probability that a person in a specific spending category during a given year will transition to another spending category in the following year. Transition probabilities are useful in projecting the distribution in the following year. Transition probabilities were produced only for the Commercial population. Four sets of transition probabilities were produced for study years 2014–2016. Transition probabilities could not be calculated for study year 2017 because that would have required 2018 data, which were not available. The transition probabilities are summarized in Tab 12 of the companion file.

- *Source Distributions*. As the name implies, a source distribution is a breakdown of the members in a spending group by their status in the prior year. Source distributions were produced only for the Commercial population. Source distributions were produced for study years 2014–2017. A source distribution for 2013 was not produced because that would have required 2012 data, which were not available. The source distributions are summarized in Tab 13 of the companion file.

- *Tables and Figures*. The development of each table in the report is demonstrated and annotated in Tabs 14 – 24. Similarly, the development of each figure in the report is demonstrated and annotated in Tabs 25 – 36.

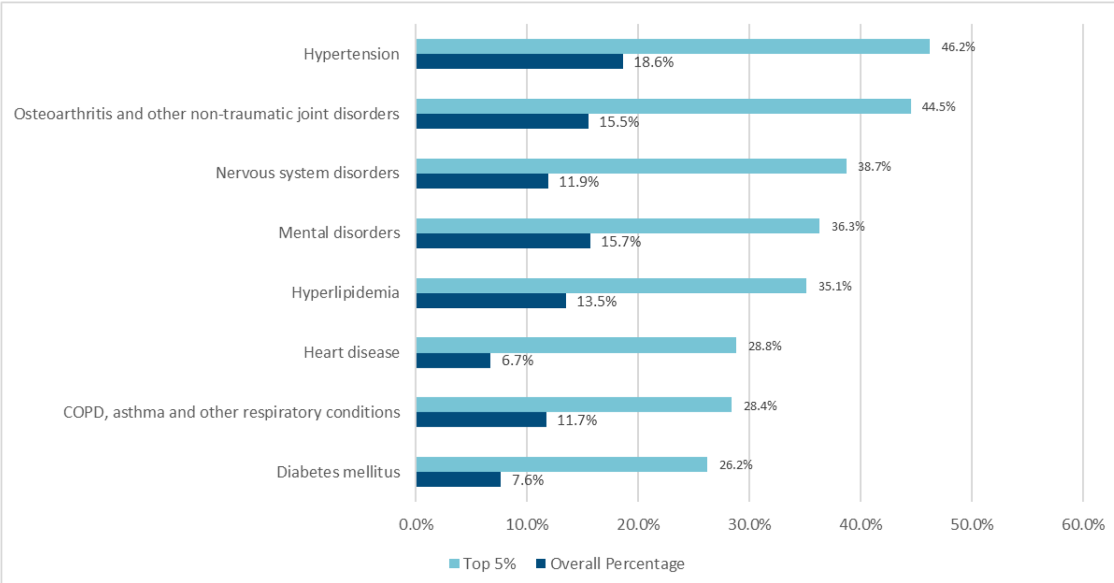
2.4 WHO ARE THE TOP SPENDERS?

As discussed above, considerable turnover occurs among the top spenders each year. Even so, it is helpful to understand the point-in-time distribution of the top spenders, especially if the results are stable year over year. Of course, the results will vary by population, but the total U.S. population results shown here provide a good starting point. This information was based on a literature review rather than an analysis of the HCCI data.

DISEASE STATE

As shown in Figure 2.11, the most common disease states among the top spenders are chronic diseases, such as hypertension and heart disease. According to the Centers for Disease Control and Prevention (CDC), a chronic condition is one that is expected to last at least one year and requires ongoing medical attention and/or limits a person's activities of daily living.[15] This result is not surprising. According to the CDC, 90% of all expenditures are for people with one or more chronic physical or mental health condition.[16]

Figure 2.11. Most Commonly Treated Conditions among Top 5% Spenders: Percentage of Persons Treated, 2019



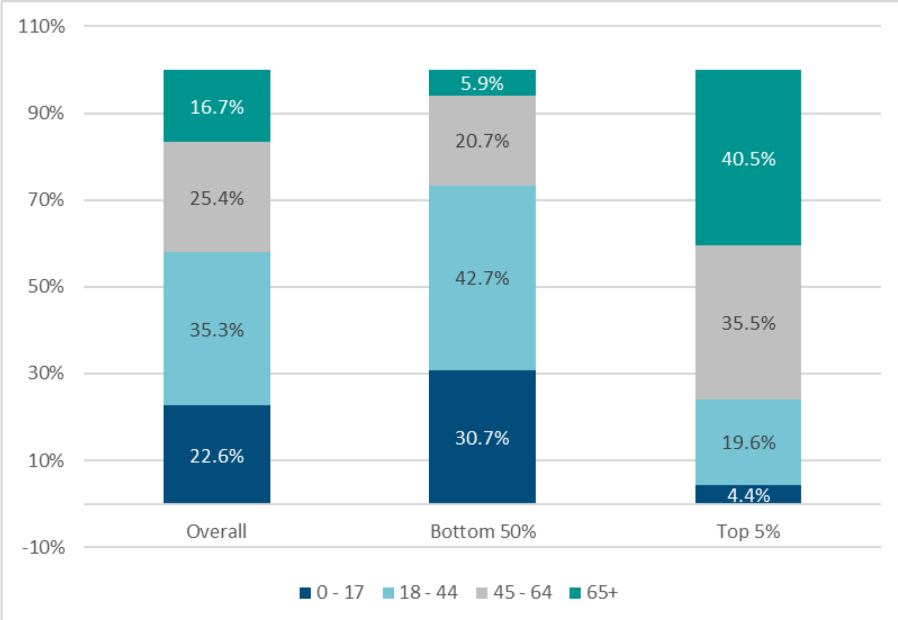
Source: Mitchell, Emily M. February 2022. Concentration of Healthcare Expenditures and Selected Characteristics of High Spenders, U.S. Noninstitutionalized Population, 2019. AHRQ Statistical Brief no. 540. *meps.ahrq.gov, https://meps.ahrq.gov/data_files/publications/st540/stat540.shtml?msclkid=48400ec0d13211ecbf44a86a0e73d4e6* (accessed Aug. 26, 2023).

Note: Comorbidities are common in chronic diseases. More than half the people with at least one chronic disease have multiple diseases.[17]

DEMOGRAPHIC DATA

As Figure 2.12 shows, 76% (40.5% + 35.5%) of all top spenders are over the age of 44.

Figure 2.12 Distribution of Top Spenders by Age

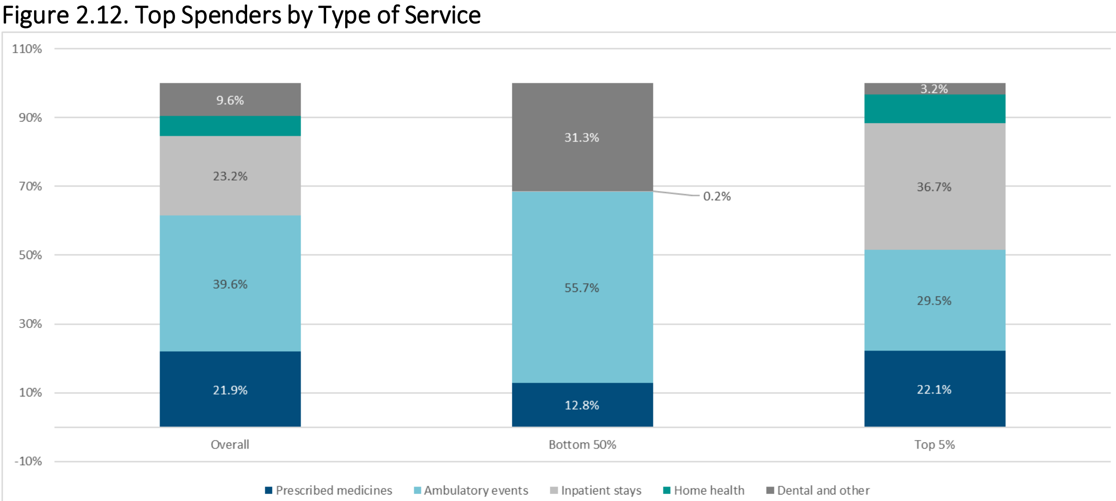


Source: Mitchell, Emily M. February 2022. Concentration of Healthcare Expenditures and Selected Characteristics of High Spenders, U.S. Noninstitutionalized Population, 2019. AHRQ Statistical Brief no. 540. *meps.ahrq.gov, https://meps.ahrq.gov/data_files/publications/st540/stat540.shtml?msclkid=48400ec0d13211ecbf44a86a0e73d4e6* (accessed Aug. 26, 2023).

TYPE OF SERVICE

As Figure 2.12 shows, at 36.7%, inpatient stays are the main cost driver for the top spenders.

Figure 2.12. Top Spenders by Type of Service

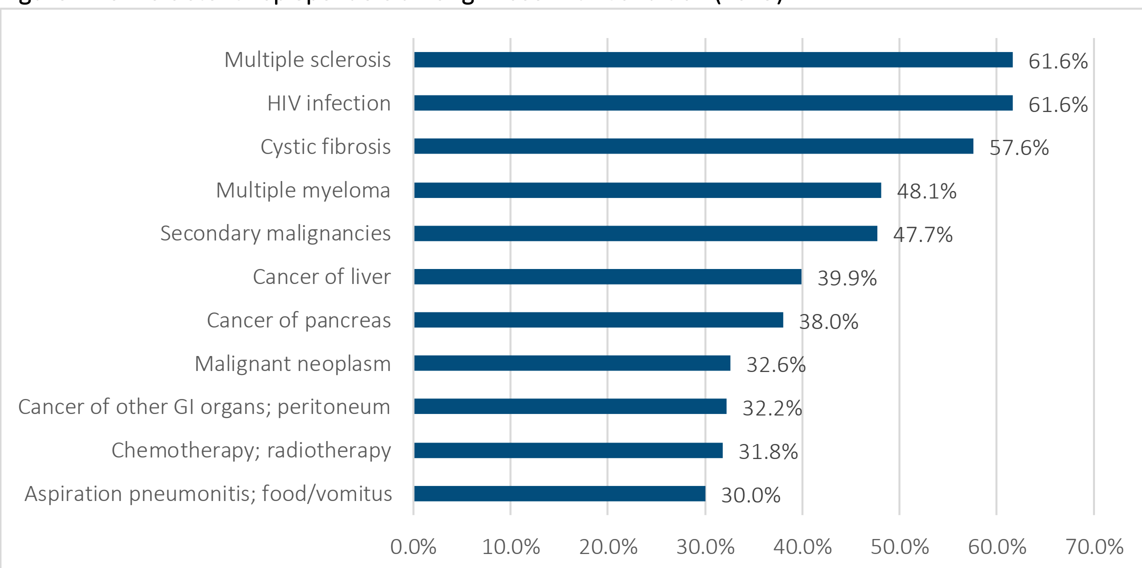


Source: Mitchell, Emily M. February 2022. Concentration of Healthcare Expenditures and Selected Characteristics of High Spenders, U.S. Noninstitutionalized Population, 2019. AHRQ Statistical Brief no. 540. *meps.ahrq.gov, https://meps.ahrq.gov/data_files/publications/st540/stat540.shtml?msclkid=48400ec0d13211ecbf44a86a0e73d4e6* (accessed Aug. 26, 2023).

PERSISTENT TOP SPENDERS

As shown in Table 2.5, about 74.6% of all top spenders in 2016 jumped to a lower spending category in 2017. What do we know about the remaining 25.4%? According to a recent study,[18] about 1.3% of all employer group members are persistent high spenders and accounted for 19.5% of total spend in 2017. This study defined persistent top spenders as members who fell into the top 5% category each year for three years. In this case the three-year period was 2015–2017. This study also noted that persistent top spenders tended to be older than other top spenders and used more inpatient and pharmacy drugs. As Figure 2.13 shows, the top three conditions that are predictive of persistent spending are HIV infection, multiple sclerosis and cystic fibrosis.

Figure 2.13. Persistent Top Spenders among Those with Condition (2015)



Source: Claxton, Gary, Mathew Rae, and Larry Levitt. July 22, 2019. A Look at People Who Have Persistently High Spending on Health Care. *healthsystemtracker.org, https://www.healthsystemtracker.org/brief/a-look-at-people-who-have-persistently-high-spending-on-health-care* (accessed Aug. 26, 2023).

BEGINNING OF LIFE, END OF LIFE

We have all seen much speculation about the impact that heroic efforts at the beginning of life and at the end of life have on the overall cost of health care. That answer, of course, depends on the population under review.

Approximately 15% of all live births result in a stay in the neonatal intensive care unit (NICU) of a hospital.[19] NICUs are sometimes referred to as special care nurseries. Common conditions treated in the NICU include anemia, breathing problems, hypoglycemia, pneumonia and heart defects. These conditions may be resolved shortly after birth or may result in long-term problems. Although these conditions may be associated with preterm deliveries and low birthweight, some conditions are congenital in nature. Risk factors include the age of the mother, multiple births, prenatal care and the health of the mother, especially if she is exposed to drugs, alcohol and cigarettes.[20] Based on the authors' experience, a NICU stay can cost over $1 million.

Estimates for the impact of end-of-life care on Medicare expenditures range from 13% to 25% depending on the underlying methods and assumptions. The higher numbers are generally associated with studies examining the last 12 months of life.[21]

Types of care considered include the following:

- *Diagnostic Care*. Diagnostic care, such as laboratory and radiology tests, is always a factor regardless of the member's age. That said, the intensity of this treatment may increase if the patient is facing a life-threatening disease.

- *Curative Care*. Once a potentially life-threatening disease has been diagnosed, the natural tendency is to restore the patient to good health through surgery, drug therapy and other means. Naturally, the patient and family will want to explore the possibility of curing the disease. In many cases the treatment will be costly. The quality of the patient's life may also suffer. Many of the treatments are painful and time-consuming.

- *Palliative Care*. An alternative to curative care is palliative care, which is also referred to as comfort care. This care is often provided through a hospice service. Hospice care may be provided at home or in a facility, such as a hospital, hospice facility or skilled nursing facility. Services may include benefits not otherwise covered such as in-home hospital beds and certain drugs for pain management, social services and spiritual or grief counseling. Medicare provides these services at little or no out-of-pocket cost to the patient if a doctor certifies that the patient's life expectancy is less than six months and if the patient agrees to forego curative care.

- *Activities of Daily Living*. As a person ages, activities of daily living, such as walking, eating and oral hygiene, become more difficult and require assistance. Medicare does cover limited benefits for this type of assistance, but the cost of care is mostly borne by Medicaid, private insurance or out-of-pocket expenditures.

Section 3: Case Study

In this section a simple case study is presented to illustrate how TRA may work in practice for a specific situation: the projected budget for a large, self-insured employer group. The decision will be based on the RV risk, projection risk and total risk. As this case study shows, TRA is usually just an overlay to an existing process.

The key take-aways from this section include the following:

- *Key Metric*. Since the budget will be defined in terms of a PMPM, this PMPM will be considered the key metric used in the analysis. Had the decision team decided to use a different key measure, such as total costs, then the analysis described below would have been slightly different.

- *The Projection Risk*. The projection risk includes the parameter risk, which is defined as the risk associated with incorrect assumptions, and the model risk, which is defined as the risk associated with the infrastructure of the model. In this case study, the parameter risk has two components: the starting value risk, which measures the reliability of the raw data being used as a foundation for the projection, and the assumption risk, which measures the ability to predict accurately the value of the assumptions underlying the projection. The assumption risk will be measured on a component-by-component basis using techniques including model-specific analysis, regression analysis and ad hoc analysis, where a component is a specific trend assumption such as average cost per service. In this case study, the assumption is that there is little or no model risk.

- *The RV Risk*. Given the consistency of the cost distributions demonstrated in Section 2, it is reasonable to assume that a cost distribution is a probability distribution function for the RV risk associated with an individual. Risk in this case study is based on a population and the population is considered a random sample, and so the Central Limit Theorem applies. That means that the RV risk will be measured using the normal distribution using the coefficient of variation discussed in Section 2.

- *The Total Risk*. In this paper, the total risk will be calculated as the weighted average of the RV risk over the entire universe of possible scenarios, where each scenario relates to a specific candidate value for the designated key value. The key value is determined as the inverse of a cumulative probability value. In this case study, only one budget PMPM was under consideration. In real life, several alternatives may be considered.

The case study used in this section is hypothetical. Actuaries and other analysts should use professional judgment to determine if the process used in this section is adequate enough to meet the Actuarial Standards of Practice. In some cases, additional analysis may be necessary to meet those standards, and in other cases less analysis may be needed. The reader is also reminded of the limitations of TRA described in Section 1.5.

3.1 THE CASE STUDY

The case study presented in this section is based on a self-insured employer health plan with 40,000 average members. The objective for this case study is to set the budget for the plan costs for the upcoming plan year expressed as a PMPM. The analysis is being performed in June of year 1. Detailed historical data are available for the three-year period before year 1 and for the first five months of year 1. In addition, the consulting actuaries for this group have maintained a summary database with the actual and projected values underlying each assumption for the past 10 years.

Actual costs exceeded the budget last year, and based on preliminary numbers, it looks like actual costs will exceed the budget in year 1, primarily because of high-cost claimants. The decision team will consider this as they set the rates for year 2. The team includes the following:

- *Benefits Manager*. The primary concern for the employer's benefits manager is to keep the benefit plans as rich as possible because their year-end bonus is determined in large part by employee satisfaction survey results. To increase employee satisfaction, the benefits manager has proposed adding additional benefits using the argument that the year 1 results are a fluke and will return to normal levels in year 2.

- *Finance Director*. The finance director, whose year-end bonus is determined based in large part on their ability to stay within a relatively tight budget, wants to ensure that the budget is adequate.

- *The Senior Vice President*. Compensation for the senior vice president (SVP) depends on a combination of employee satisfaction, staying within budget and keeping the budget as low as possible to allow more money to be spent on the business. The SVP is the final decision-maker in this process.

The employer has asked their consulting actuary to perform underlying analysis once again for the current year, including an analysis to determine the impact of proposed benefit changes on the overall costs and predictability of the results. Although no bonus is associated with this work, the actuary sees the need to provide value to the process to keep the client happy in hopes of future work. The actuary has recommended that the team use TRA for the first time this year. The team has agreed as long as the consulting actuary stays within the consulting budget.

To make the best use of the available resources, the actuary met with the team before starting their work to provide some background on TRA and to gain some understanding of how TRA may be applied in this case. As a result of these discussions, the actuary and the team agreed to assume that, with the exceptions noted below, the employer did not expect any major changes to the current plan. In their final report, the actuary will document other potential risks discussed with the client but disregarded. Specifically, the employer agreed to assume that the membership would hold at 40,000 throughout the year. That number may indeed fluctuate, but the employer's financial processes and bonus structure can easily adjust if that occurs. The exceptions are the following:

- *Benefit Changes*. The recommended benefit change is to lower the copay for primary care physicians. The estimated increase in costs for this change is $2 PMPM, which includes assumptions about the increased number of primary care visits due to the lower copay and the offsetting costs from members choosing to use a lower cost primary care doctor rather than a more costly specialist. The actuary has explained that the risk includes the possibility that more PCP visits will occur than anticipated and less movement away from specialists than expected.

- *New Blockbuster Drug*. The Food and Drug Administration is expected to approve a new drug that will provide considerable relief to patients with a rare disease sometime in year 2. The risk includes the timing of the approval, the prevalence of people with the disease in year 2, the percentage of patients with the disease who actually take the drug, and, of course, the cost of the drug.

- *Provider Negotiations*. The plan administrator has notified them that they are negotiating with several hospitals used frequently by the employer's members. Because the negotiations are ongoing, little information is available about when negotiations will be complete and what the outcomes will be. Although the information about the negotiations is incomplete, the team and the actuary can set a range of possible values based on similar negotiations from the past and information supplied by the plan administrator about the negotiations.

Based on these assumptions, the actuary has recommended a best estimate PMPM of $500 with a PAD of 2.5% or $12.50. This means that the proposed budget number will be $512.50 ($500.00 + $12.50).

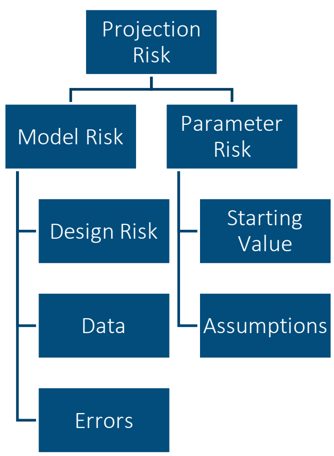
3.2 THE PROJECTION RISK

As the name implies, projection risk is the risk associated with missing an estimate of a key metric, which in this case study is the projected year 2 PMPM. By definition, the projection risk analysis consists of identifying all the possible projection outcomes for a key variable and the associated probabilities of that outcome. The goal is to produce a projection risk probability distribution table for use in calculating total risk.

THE PROJECTION RISK FRAMEWORK

The name of the game is total risk, and so the first step in the process is to provide a risk framework for this case study to make sure that all the projection-related risks are accounted for, such as the one shown in Figure 3.1.

Figure 3.1. Projection Risk Framework



The model risk represents the risks associated with the infrastructure of the underlying models and processes used to do the projection. The primary type of model risk is often the design risk, which is defined as the risk associated with a model or process that does not serve the intended purpose.[22] The best way to assess the design risk is to perform a qualitative process review to determine if the model is meeting its intended purpose and if the data and calculations underlying the process meet actuarial standards.

Two types of risk are associated with the parameter risk in this case study: the starting value risk and the assumptions risk. The starting value risk is the risk associated with choosing a starting point for a projection that is not statistically reliable. As the name implies, the assumption risk is the risk associated with setting the projection parameters.

The framework shown in Figure 3.1 intentionally excludes certain types of risk associated with the total cost of the benefit plan. In this case study, the SVP has agreed to exclude these risks from the analysis at hand:

- *Other Employee Benefits Considerations*. This study focuses just on the claims cost associated with an employee benefits program for simplicity. Other costs associated with an employee benefits program, such as administrative costs, monthly contributions and wellness rewards, are considered out of scope for this case study.
- *Catastrophic Events*. Catastrophic events, such as the COVID-19 pandemic and hurricanes, are also considered out of scope for this case study given the low frequency of such events and the difficulty of projecting the associated costs, much less the associated variance.
- *Bias*. Increasing attention is being given to analyzing the impact of bias in analytics. This could include bias in the choice of data, methods and/or specific assumptions. Although this is an important topic, it is too broad for this paper.

THE MODEL RISK

According to ASOP 56, model risk is defined as "the risk of adverse consequences resulting from reliance on a model that does not adequately represent that which is being modeled, or the risk of misuse or misinterpretation." The analytical process relating to design risk is to review a model for potential sources of risk and to correct those determined to be material to the extent it is possible. If it is not possible to quantify or correct a weakness in the model, then that weakness should be identified and communicated to any intended users[23]. The process underlying the projections for this case study is shown in Table 3.1.

Table 3.1. Case Study Process Review

Purpose	Row	Description	Value	Risk Type	Methodology/ Calculation
Complete Year 1	a.	Claims incurred YTD in Year 1	$ 440	Starting Value	Experience data
	b.	Completion Factor	1.0%	Assumption	Model-specific review
	c.	Partial Year Trend	5.0%	Assumption	Model-specific review
	d.	Year 1 Projected Claims PMPM	$ 467	Model	a. x (1+ b.) x (1+ c.)
Estimate Core Trend	e.	Unit Costs	4.0%	Assumption	Regression analysis
	f.	Utilization	0.6%	Assumption	Regression analysis
	g.	Mix and Severity	0.5%	Assumption	Regression analysis
	h.	Core Trend	5.1%	Model	(1 + e.) x (1 + f.) x (1 + g.) - 1
Estimate Non-Core Trend	i.	Major Provider Negotiations	0.4%	Assumption	Ad hoc review
	j.	New Technology/Drugs	0.2%	Assumption	Ad hoc review
	k.	Non-Core Trend	0.6%	Model	(1 + i.) x (1 + j.) - 1
Group Specific Changes	l.	Population Aging	0.8%	Assumption	Ad hoc review
	m.	Benefit Changes	0.4%	Assumption	Ad hoc review
	n.	Group-Specific Changes	1.2%	Model	(1 +l.) x (1 +m.) -1
	o.	Net Trend	7.1%	Model	(1 + h). x (1 + k.) x (1 + n.) -1
Determine Year 2 PMPM	p.	Best Estimate Year 2 PMPM	$ 500	Model	d. x (1 + o.)

Once the year 1 PMPM ($467 from row d) and the trend rates (7.1% from row o) have been established, the final PMPM can easily be estimated as $500 = $467 × 1.071. The actuary considers the $500 PMPM shown in row p. to be the best estimate. The actuary has recommended a provision of 2.5% of the best estimate or $12.50 PMPM. The budget PMPM will be the best estimate plus the provision for adverse deviation or $512.50 ($500.00 + $12.50). The annual budget as a dollar amount is $246 million ($512.50 × 12 × 40,000).

The development of the values follows standard actuarial practice.[24] That said, the details behind those calculations are not shown here. A few comments about the calculation:

- *Year 1 Estimation*. Because only five months of data are available in year 1, the data incurred in the first five months must be completed to account for claims paid after the data were gathered. The completed data for the first five months must be trended to project a complete estimate for year 1. Both elements are estimated using models specifically designed for that purpose.

- *Core Elements*. Core elements are components of the net trend that should be considered in each annual trend calculation. In this case study, the assumption is that the data underlying these elements are stable enough to rely on for future projections. Except for the utilization projection, the trends will be using regression analysis based on past history. Utilization, on the other hand, depends on factors external to the employer group, such as inflation and unemployment. In all likelihood, the economic model also will be based on regression analysis.

- *Non-Core Elements.* Non-core trend elements are those elements requiring an ad hoc analysis. The most common examples are new drugs and technologies. For example, if a new blockbuster drug is introduced, various questions need to be answered, including “How much will the drug cost?” “How many people will use the drug?” and “Is this a new drug or an improvement over an existing drug?” The data needed to answer these questions will come from various sources, including data supplied by the manufacturer.

- *Group-Specific Changes*. Both core and non-core elements of trend reflect expected changes to claims costs that are happening regardless of any actions taken by the group. In this case study, only two changes are considered, a benefit change and the aging of a rather stable population. Both elements were calculated using an ad hoc analysis, meaning that the results may not be symmetrical around the mean.

After reviewing this table and discussing it with the decision-making team, the actuary has determined that they face little model risk. The calculations consider all known risks, except for the risks considered outside the scope of this analysis, as discussed above. In keeping with actuarial standards, the scope was agreed to at the start of the project and will be noted again in the final report. The actuary also performed a due diligence review of the underlying data and models to ensure that they could be relied on in this process.

THE PROJECTION RISK

The values shown in Table 3.1 can be estimated using standard actuarial methods.[25] Techniques for measuring the variance associated with each value will depend on the method used to estimate the value shown in Table 3.1.

Starting Value Risk

The source for the number in row a is raw data, so at first glance it may appear that the number is “fixed” with no expected variance. The problem is that the experience PMPM represents a sample drawn from the overall population, so it will have some variance, and that variance can be estimated using the Central Limit Theorem, as discussed in Section 1.5.

In this case the assumptions will be that the population mean is equal to the PMPM mean of $440, which is standard practice, and the coefficient of variation is 5.0, which is the 2017 coefficient of variation, trended to the current period. The standard deviation is then 2.5% (5.0 ÷ square root of the average members = 5.0 ÷ √40,000 = 5.0 ÷ 200 = 2.5%).

Assumption Risk
Each assumption in Table 3.2 is estimated using standard actuarial methods and is subject to variance. Techniques to measure the variance depend on the methodology used to determine the value used in Table 3.1. In this case study, three main techniques are used. The techniques for defining the values given below are outside the scope of this paper.

- *Model Specific*. Most completion and seasonality factors are developed using stand-alone models that reflect past claims payment patterns and incurred PMPMs, adjusted for future experience. As in most models, the result is a possible range of values from which the analyst can choose. The variance can be estimated by weighting the ranges to develop the projection weights. The result may or may not be normally distributed based on the information available. In this case study, the assumption is that the variance is normally distributed with a standard deviation of 1% for the completion factor and 5% for the partial year trend.
- *Regression Analysis*. Core elements are, by definition, trend components that can be projected safely using experience, usually through some type of regression analysis. In that case, the standard error, which will be approximately normally distributed in most forms of linear regression, can be used to determine the variance. In this case study, the assumption is that the standard error is 5%.
- *Ad Hoc Analysis*. Not everything in health insurance is normally distributed. This is especially true for non-core trend elements, such as a major provider renegotiation, and benefit changes, which tend to either add to costs or subtract from costs, depending on the nature of the change. In this case study, the variance was determined as part of the assumption-setting process.

THE PROJECTION RISK TABLE

The development of the projection risk table requires some simplifying assumptions to make the process manageable, starting with a simple recap of the findings described above as shown in Table 3.2.

Table 3.2. Recap Table

Row	Description	Table 3.1 Net Trend	Cumulative PMPM	Net PMPM	Std. Deviation Percentage	Std. Deviation $ Amount	Row in Table 3.1
		Col. 1	Col. 2.	Col. 3.	Col. 4	Col. 5	Col. 6
a.	Starting Value	N/A	440	$ 440	2.5%	$ 11.00	a.
b.	Completion Factor	1.0%	444	$ 4	1.0%	$ 0.04	b.
c.	Partial Year Trend	5.0%	467	$ 22	3.0%	$ 0.67	c.
d.	Core Trends	5.1%	491	$ 24	5.0%	$ 1.20	h.
e.	Non-Core Trends	0.6%	494	$ 3	N/A	N/A	k.
f.	Group-Specific Changes	1.2%	500	$ 6	N/A	N/A	n.
g.	Total PMPM			$ 500			

A few comments about this table:

- *Net Trend.* The net trend values correspond to the values in Table 3.1. The row references are shown in Column 6.
- *Cumulative PMPM*. The cumulative PMPM in Column 2 is derived by applying the trend shown in Column 1 to the value in the previous row. For example, the $444 shown in row b of Column 2 is derived by multiplying $440 (row a, Column 2) by 101% (100% + 1%) using the trend in Column 1, row b.
- *Net PMPM*. The net PMPM is derived by decomposing the cumulative PMPM shown in Column 2. For example, the $4 net PMPM shown in row b, Column 3 is simply $444 – $440, where $440 is the value in row a of Column 2, and $444 is the value in row b of Column 2.
- *Standard Deviation Percentage*. Rows a through d in Column 4 are assumptions derived from the development process. That work is not shown here. No standard deviations are shown for rows e and f because those values were not derived using regression analysis or any similar methodology.
- *The Standard Deviation Amount*. For the applicable rows, this value is simply Column 3 × Column 4.

Now that the recap is complete, the next step is to determine the structure of the projection risk table. The first decision is to determine whether to use the left-hand side of equation 1.1, using the key metric as the independent variable, or the right-hand side of the equation, using the cumulative probability distribution. In this case study, we have several elements of trend, each with its own variance, so it will be easier to sum over all possible probability values. The second decision is whether to use integrals such as the ones shown in Equation 1.1 or to approximate the values using histograms. In this case study, histograms will be used because they are easier to explain and they provide valuable detail. If histograms are used, then the final decision is how to parse the probability range by scenarios. There is no hard and fast rule about choosing scenarios. Instead, the choice should be based on what makes sense under the circumstances. In this case study, the probability range is divided into five scenarios that correspond to how many standard deviations the value is from the mean. This was done to make it easier for the reader to reconcile concepts. Now that the structure has been established, the values for the table can be populated, as shown in Table 3.3.

Table 3.3. Projection Risk Table

Row	Description	Projection Element	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Combined
a.	Scenario Description		2+ Std Devs Below Mean	1 to 2 Std Devs Below Mean	+/- 1 Std Dev From Mean	1 to 2 Std Devs Above Mean	2+ Std Devs Above Mean	
b.	Probability Distribution		2.3%	13.6%	68.3%	13.6%	2.3%	100.0%
c.	Cumulative	Lower Bound	0.0%	2.3%	15.9%	84.1%	97.7%	0.0%
d.	Distribution	Upper Bound	2.3%	15.9%	84.1%	97.7%	100.0%	100.0%
e.		Midpoint	1.1%	9.1%	50.0%	90.9%	98.9%	50.0%
f.	PMPM	Starting Value	$ 415	$ 425	$ 440	$ 455	$ 465	$ 440
g.		Completion Factor	$ 4	$ 4	$ 4	$ 4	$ 5	$ 4
h.		Partial Year Trend	$ 21	$ 21	$ 22	$ 23	$ 24	$ 22
i.		Core Trends	$ 21	$ 22	$ 24	$ 26	$ 27	$ 24
j.		Non-Core Trends	$ -	$ 2	$ 3	$ 4	$ 5	$ 3
k.		Group-Specific Changes	$ 4	$ 5	$ 6	$ 8	$ 10	$ 6
l.		Total PMPM	$ 465	$ 480	$ 500	$ 520	$ 535	$ 500

A few comments about these calculations:

- Rows a. and b. were determined in designing the structure of the table.
- Rows c., d., and e. are used to determine the midpoint value for each scenario.

- Rows f. through i. are calculated as the inverse of the midpoint value, given the mean and standard deviation from Table 3.2. For example, the $415 value shown in Scenario 1 row f is the inverse of the probability value of 1.1% for a normal distribution with a mean of $440 and a standard deviation of $11. In Excel, the formula is NORM.INV(.011,440, .025 × 440). Rows j and k are not based on a normal distribution. Instead, they are based on an ad hoc study not shown in detail here.

In terms of estimating the total risk, the key numbers can be found in row b. and in row l. That said, the additional information in this table may provide the SVP with some valuable insights:

- *Stop Loss*. The data underlying this study is considered fully credible because the projection was based entirely on the group's own experience. That said, a 2.5% standard deviation results in a wide range of values. The SVP may want to consider a stop-loss contract to reduce that variance. Stop-loss analytics are outside the scope of this paper.

- *Model Specific.* The SVP may want to ask the actuary to take a closer look at the model-specific calculations to determine if the variance can be lowered. They may also want to look at payment-timing statistics to determine if claims are being paid quickly enough.

- *Benefit Changes*. Although considerable internal discussion took place about the value of a benefit change, Table 3.3 indicates that the impact will be minimal.

3.3 THE RANDOM VARIATION RISK

The process for determining the RV risk is first to determine the applicable risk measures, choose a cost distribution, then calculate the risk for each value of the key metric. This is step 3 in Figure 1.3.

RISK MEASURES

The RV risk is measured using specified risk measures, which are tied to the objectives of the decision-making team. The actuary has recommended three measures:

- *Expected Budget Excess/(Shortfall)*. The SVP will want to know how much the actual PMPM costs will be over or under the budget for both decision-making and for budgeting purposes. This metric is a PMPM measure. This number can be easily calculated by subtracting the expected PMPM in the scenario from the budget. For example, in Scenario 5 this number is $512.50 – $535 = –$22.50.

- *The Probability of Exceeding the Budget*. This metric will help the SVP understand whether the total budget of $512.50 (best estimate + PAD = $500.00 + $12.50 = $512.50) is adequate or not. This number is the complement to achieving the budget. In Excel, the formula for Scenario 2 is 1 – NORM.DIST($512.50,$480,2.5% × $480, TRUE) = 0.1%. Similarly, for scenario 4, the probability of exceeding the budget is 73.9%. Figure 3.2 illustrates these values visually.

- *The Probability of Exceeding the Budget by More than $6 Million*. In the previous budget, the SVP used a 5.0% PAD, which translates to $25.00. The PAD this year is only $12.50, so the SVP wants to understand how much additional risk they are taking. The $6 million dollar amount was calculated as $6 million = ($25.00 – $12.50) × 12 × 40,000. The Excel formula is the same as the formula above, except the budget number of $512.50 has been replaced by $525.00.

Figure 3.2 illustrates the concept of RV risk. This graph shows the expected risk under Scenario 2, which is based on the assumption that the actual mean will turn out to be $480. In that case, the budget of $512.50 is 2 standard deviations from the mean of $480, so the chances of exceeding the budget just due to random variation is only 0.4% using the appropriate statistical formulas.

Figure 3.2.
EXPECTED MEAN = $480, BUDGET = $512.5

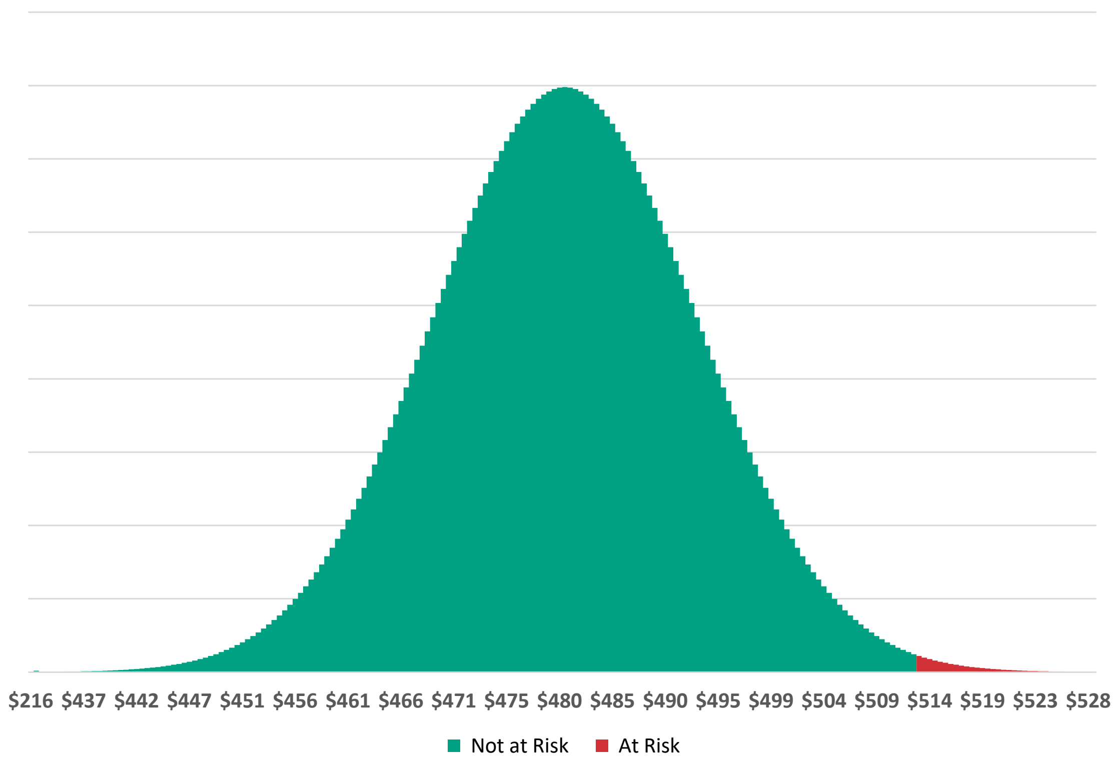
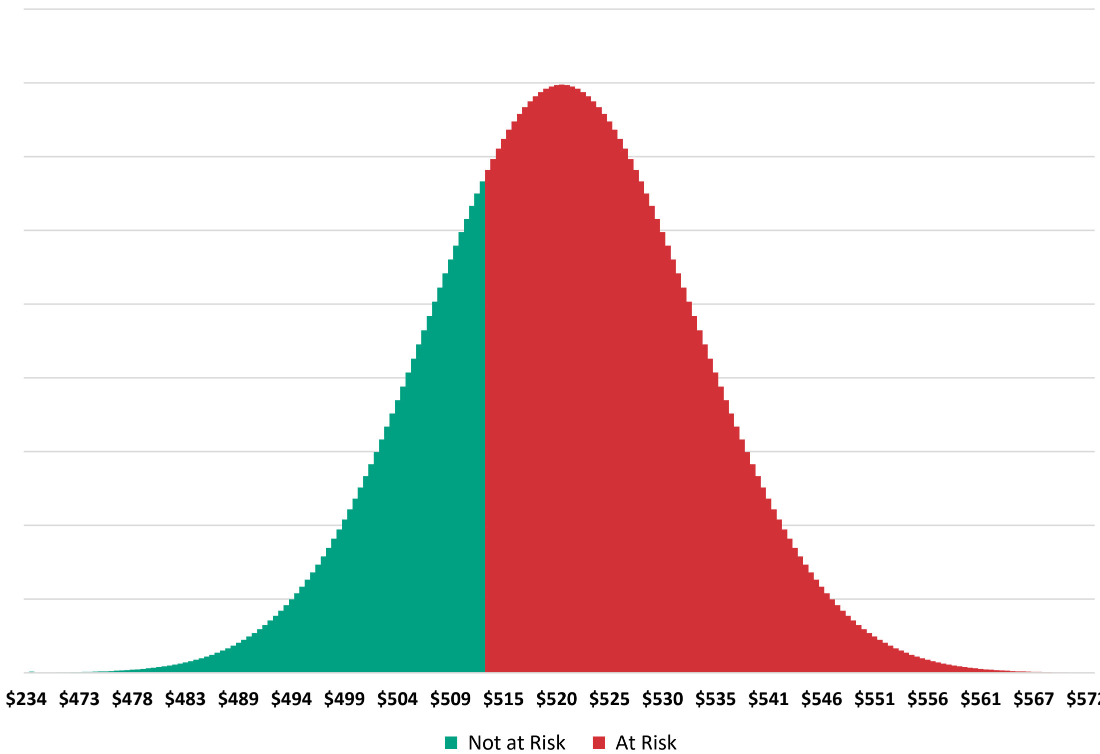


Figure 3.3 reflects Scenario 4, where the mean turns out to be $520. Since $520 is already above the budget, then the probability that results exceed the budget is 71.5% using the statistical formulas. One note. Both Figures 3.2 and 3.3 are based on histograms, which approximate the normal distribution. As a result, there may be slight differences between the statistical formulas and the results shown in the output table included in row b of the Output table in the model included in the Companion File.

Figure 3.3
EXPECTED MEAN = $520, BUDGET = $512.50



OTHER RISK MODELS

The primary difference between TRA and other risk models is that TRA reflects both the projection risk and the random variation risk. Other models, such as the individual risk model and the collective risk model, focus just on the RV risk. Specifically, both the individual risk model and the collective risk model are based on Equation 3.1.

Equation 3.1.

$S = X_1 + X_2 + \cdots + X_N$, $N = 0, 1, 2, \ldots$

where $S = 0$ when $N = 0$.

In both models, the X_j's are independent random variables. In the individual risk model,

- N is a constant value that represents the number of unique members in the health plan.
- The distribution for each of the X_j's may vary from member to member.

In the collective risk model:

- N is a random variable whose distribution is not related to the X_j's. N represents the number of claims. In this context one may find multiple claims per member.
- The X_j's are i.i.d., that is, they are independent of one another and have the same distribution, mean and variance. The X_j's represent the severity of the claims.

The RV risk in the TRA model may be viewed as a special case of the individual risk model, where *N* is the number of unique members in the population during the period in question and the X_j's are random variables determined by the cost distributions. Similarly, the RV risk is consistent with the collective risk model assuming that *N* is a random variable with a constant value. Either way, *S* is converted to an average PMPM.

3.4 THE TRA TABLE

Using the techniques described below, the actuary presented Table 3.4 to the decision team. During the meeting with the employer, the actuary carefully explained the process and the rationale for each decision made in the analysis.

Table 3.4. Risk Analysis for Best Estimate = $500.00, Budget = $512.50

Row	Description	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Combined
a.	Scenario Description	2+ Std Devs Below Mean	1 to 2 Std Devs Below Mean	+/- 1 Std Dev From Mean	1 to 2 Std Devs Above Mean	2+ Std Devs Above Mean	
b.	Probability Distribution	2.3%	13.6%	68.3%	13.6%	2.3%	100.0%
c.	PMPM	$ 465	$ 480	$ 500	$ 520	$ 535	$ 500
d.	Expected Excess/(Shortfall)	$ 47.27	$ 32.12	$ 12.63	$ (7.39)	$ (22.54)	$ 12.54
e.	Probability of Exceeding Budget	0.0%	0.4%	15.6%	71.5%	95.4%	15.1%
f.	Probability of Exceeding Budget by More Than $6 Million	0.0%	0.0%	2.2%	34.7%	77.4%	8.0%

The key points the actuary made during the presentation included the following:

- There is a 15.1% chance that actual claims will exceed the budget (the total column for row e).
- If the budget number is set at $525.00 by using a 5% provision for adverse deviation, then the chance of exceeding the budget is only 8.0% (row f for Total Risk) versus 15.1% for the current budget (row e for Total Risk).

At the end of the presentation, the actuary made two recommendations. First, the actuary recommended that the employer ask their administrator for a trend guarantee. Under a trend guarantee, if the employer's trend exceeds an amount specified in advance, then the administrator would reimburse some or all of the administrator's fees. It is unlikely that the administrator's fees would entirely offset the additional costs, but it would ensure that the administrator had a financial stake in keeping costs down. The actuary also recommended that the team consider stop-loss insurance to reduce the expected variance. The team agreed to those changes for the next year.

Before leaving, the team asked how they would know at the end of year 2 whether or not the original best estimate of $500.00 was right. The actuary replied that they would not know exactly, but they could quantify the odds using the techniques described above. For example, if the actual year 2 PMPM turns out to be $512.50, the probability of the PMPM being that high or higher if the original PMPM best estimate of $500 is correct is 15.6% (Scenario 3, row e).

Section 4. Areas for Further Development

Although the focus of this report has been on the application of TRA to health care costs, the general principles should apply in any situation involving two-dimensional risks. Some examples are discussed in this section. The concepts behind these examples need to be developed further before they become part of a normal workstream. In some cases, this will occur organically as analysts apply the principles in their day-to-day work and then share the results through webinars, meeting sessions and articles. In other cases, formal, funded research will be required.

4.1 REPORT FOLLOW-UPS

Several areas for further study relating to the projection of health care costs have been identified in this report. These items are discussed in more detail below.

VALIDATION OF ASSUMPTIONS

TRA depends on the assumption that PMPMs are basically a random sample from a hypothetical population. As noted in this report, the authors have tested this theory often and found that it tends to be true, or, at least true enough to be useful. Such research may show that this quality does not apply to every population. In that case, it would be helpful to understand when it applies and when it does not. In circumstances in which it does not, it would be helpful to explore alternative methodologies.

To keep things simple and easy to explain, the authors based the standard deviation calculations on average members. In most cases, this seems reasonable because, by definition, average members = unique members × average duration. The problem is that the duration is not constant by bracket, so one can find a material difference, especially in stop-loss calculations.

ADDITIONAL AND UPDATED DISTRIBUTIONS

The cost distributions, transition probabilities and source distributions presented in this paper need to be updated to a post–COVID-19 level. Also, it may be desirable to develop distributions for other key populations, such as Medicaid. Similarly, some subgroups of a population may have quite different means and distributions than the population as a whole. Two key groups that come to mind are persistent top spenders and the chronic illness population. As part of this effort, it may be helpful to do deeper dive into the characteristics of the top spenders by, for example, age or disease state.

MODEL RISK

The example shown in Section 3 was straightforward enough that it was safe to assume no model risk. That is not always the case. For example, if the analysis applies to the insured group business for an MCO, then group-specific rates are based on a multistep process in which each step builds on the previous step, usually by applying rating factors to the previous result. At any point in the process the calculations may not achieve the intended purpose of that step, resulting in design risk. Similarly, rating factors are based on broad book averages, so the impact will be overstated for some groups and understated for other groups, creating more variance in the estimates.

STARTING VALUE RISK: EXPANDING CREDIBILITY THEORY

In Section 3, the assumption was that the starting value in the projection was fully credible; that is, the historical experience was an acceptable starting point for the projection. That certainly would not have been the case for a group of only four members instead of 40,000. A group with four members, on the other hand, would be considered fully noncredible. It is common industry practice to apply the greatest accuracy method[26] to groups that are not considered fully credible or fully noncredible. Under this method the credibility-adjusted rate is the weighted average of the group's experience with some type of portfolio rate. In health insurance, the portfolio rate is often referred to as a manual rate. Even though this method is widely accepted, concerns about how to measure the accuracy and variance created by blending rates need to be explored. Similarly, alternative techniques should be investigated. Regardless of the method used, techniques for determining the accuracy and variance of the results need to be developed and employed.

ASSUMPTION RISK

In Section 3, techniques for determining the distribution for each parameter risk were based entirely on simple linear analysis. Techniques for determining those distributions for more sophisticated regression analysis techniques, such as multilinear regression analysis, generalized linear models and logistic regression analysis, need to be developed. Similarly, methods for improving analytics for non-core elements may need to be taken up.

4.2 ADDITIONAL CASE STUDIES

This report includes only one case study, but several other case studies can be developed using the basic principles described in this report. Additional research, however, will be required to support the applicable projection risk and, in some cases, to build additional cost distributions.

STOP LOSS

Stop-loss insurance is an important element of risk management, especially for smaller employer groups. Although the details were not provided in this report, the techniques described in the paper along with the data in the companion file can be used to determine how much stop-loss reinsurance a payer needs and the expected financial impact. On the other hand, stop-loss insurers may need to supplement this approach with other techniques, such as the negative binomial distribution, and more recent claims data to price the premiums and analyze their own risk.

PORTFOLIO MANAGEMENT

From a risk perspective a big difference is found in the risk associated with a self-insured employer group, such as the group from the case study, and an insured employer group. If the group is self-insured, then the employer bears the risk, with the possible exception of stop-loss and trend guarantees. For insured employer groups, all the risk is borne by the MCO. The MCO is faced with the challenge of setting premiums high enough to ensure that the MCO has enough funds to meet its obligations but low enough to ensure that the employer groups are not tempted to leave the MCO in search of lower premiums. The rate-setting process for this block of business is very complicated because the MCO must not only project the overall level of claims for the book, but also consider the credibility level of each group, the accuracy and the variance associated with the rating factors used to set the premium.

TRA may be helpful in providing MCOs with additional approaches to meeting these challenges. For that to happen, however, additional research is needed to provide techniques to help the MCO answer questions such as "If a group has better than average experience this year, is that predictive of future experience or was it all just due to random variation?"

REGULATORY-MANDATED PROJECTION METHODS

Many blocks of business, such as Medicare Advantage, have to follow a combination of state and/or federal formulas to project future costs. The variation underlying these required techniques may or may not be material. Further study is required.

ALTERNATE PAYMENT METHODS

With health care at 18% of GDP in 2021,[27] concerted efforts are underway to move to alternate payment methods (APMs) aimed at encouraging providers to reduce costs and increase quality. The Health Care Payment and Learning & Action Network has developed an APM framework with four reimbursement categories in an effort to achieve these goals.[28]

The first category is, of course, fee-for-service (FFS), which basically means that a provider's reimbursement is based solely on the services rendered without a link to cost or quality. A specific goal of the APM framework is to move away slowly from FFS to a payment system that provides financial incentives or penalties based on meaningful cost and quality measures.

The second category is FFS with a link to quality and value. Under this type of arrangement, a provider is paid on an FFS basis during the year and then is eligible for a bonus or penalty at the end of the year. The bonus is often based on a scorecard. The measures underlying the scorecard may reflect quality measures such as access to care and adherence to evidence-based medicine. To project the total risk associated with a scorecard, the mean and variance of each measure need to be determined and then combined at the end of the process.

The third category is similar to FFS in that reimbursement is based on services performed. Under one common variation of this APM, instead of a specific service, such as an office visit, the reimbursement is based on an episode of care, such as the entire course of treatment associated with a knee surgery. Under this category, expected costs also can be projected using regression analysis. Attention to detail is important in this case because the process is not as simple as an FFS reimbursement process. For example, under FFS most payments are based on what happens in a single day: an office visit, a surgery, a day in the hospital and so on. An episode of care, on the other hand, can last over a period of several months. Depending on the purpose of the projection, this may be important.

The final category is population-based methodologies. Under this APM, providers are reimbursed on a population basis rather than an individual patient basis using techniques such as a global budget. The techniques described in Section 3 can be adapted to estimate the TRA in these situations. One of the key challenges in applying TRA techniques in this context will be the ability to determine if the cost distribution for the population in question varies materially from the general population.

RESOURCE MANAGEMENT

In the United States payers cannot charge more based on the health status of a member. A payer can, however, reach out to members who have a specific set of conditions or who are likely to develop those conditions to make sure the member has the resources to manage their condition as best they can. The outreach may range from being as simple as an annual mammogram reminder to as intense as one-on-one counseling with a qualified professional. Regardless of the nature of the outreach, the goal will be to either keep the member healthy, manage an episode of care from both a quality and cost perspective, or prevent the progression of a disease. Every payer intervention requires resources to develop, implement and monitor the outreach.

Today, interventions are often measured on a one-time basis using studies that rely on techniques such as clinical trials, before and after studies, and participant/nonparticipant studies.[29] Although these studies are extremely useful, a need also exists to review results on an ongoing basis as new information accumulates. One way to do that is to use transition probabilities as described below.

Identifying Target Populations
So, if prior spending categories are not a good predictor of future spending for an individual, what is? Rosenberg has shown that cluster analysis can be used to develop profiles for members likely to be a top spender in the next year.[30] In her analysis, key predictors include combinations of factors, such as age, gender, ethnicity and health status. Once the profiles are in place, transition probabilities are developed for each profile, and then resources can be prioritized based on the size of the cluster, transition probabilities and expected savings. The Rosenberg paper applies to a large, diverse, population, but this concept also can be used to identify members who are the most likely to transition to a more severe disease state, such as members likely to have a knee replacement or a heart attack in the near future.

Artificial intelligence is also an analytical technique that can be used for this purpose. Like cluster analysis, artificial intelligence is a machine-learning method. In other words, instead of programming a specific algorithm, the programmer inputs a set of parameters and instructions. The computer then repeatedly acts on this information until an optimal solution is determined. As more information becomes available, presumably, the better the results.

The projection risk in this case may need to be defined slightly differently than in the previous examples discussed in this paper. In those examples, one always has the assumption of a single number that represented the “right answer.” In most of this paper that single number was the PMPM for a specific period and population. In both cluster analysis and artificial intelligence, one finds no single number that represents the right answer. Instead, both analytical techniques simply group members of a population based on specified parameters. That means that the projection risk is relative to an optimal grouping. Determining how to define and measure an optimal grouping requires further study.

Transition Probabilities
Once each population member has been assigned to a cluster, the question becomes “What will be the cost for the members in each cluster next year?” This question can be answered using transition probabilities and the methodology described in Section 2. Both a projection risk and an RV risk are associated with this process. These concepts need to be researched, and quantitative methods need to be developed.

Setting Priorities
Once the clusters have been set and the transition probabilities and the corresponding source distributions have been calculated, then resources can be allocated based on the organization’s objectives. For example, if the objective is to reduce the number of high-cost claimants, then the intervention that results in fewer transitions to that spending category can be identified. Once the intervention is identified, then the cost of that intervention can be determined and compared to other interventions to determine the priority for the organization.

4.4 GENERAL INSURANCE

The industry sells several types of general insurance, each requiring a specific type of TRA. For example, car insurance is very close in nature to health insurance with one major difference. In health insurance most deductibles are annual deductibles and priced accordingly. Most car insurance deductibles, on the other hand, are on a per occurrence basis and priced accordingly. This implies that the TRA process described in

Section 3 can be adapted for automobile insurance, but the RV risk must be calculated in a way that reflects the possibility of multiple accidents in a policy year.

At the other extreme, many general insurance policies cover risks that are low frequency but high cost, such as medical malpractice policies. In theory, TRA applies to these types of risks, but the process of determining the methodology will vary greatly by the nature of the risk and the availability of the data.

4.5 MULTIYEAR RISKS

The timeframe for health insurance is one year. For virtually all plans, benefit packages are updated once a year, members reevaluate their plan options at least once a year, and premiums and budgets are set once a year. Many risks, however, accrue over time, and the circumstances surrounding the risk also change over time. Those potential circumstances need to be reflected in the estimated risk at any point in time.

INDIVIDUAL LIFE INSURANCE

Individual life insurance premiums are set when a policy is issued, and they usually remain fixed over the life of the policy. In some cases, the premium is a level amount that does not change over time, and in other cases the premiums are defined in terms of a fixed schedule of benefits. Two major sources of risk are associated with an individual life insurance policy: the investment risk, which is addressed below, and the mortality risk, which is discussed here.

Individual life insurance premium calculations are based on mortality tables. The random variation associated with a mortality table can be easily calculated for any given year because mortality rates follow the binomial distribution. The binomial distribution serves as the analog to cost distributions in health insurance.

The projection risk can be determined using various scenarios for the mortality tables. The materiality of the projection risk depends in part on the term of the policy. In recent years, life expectancy has decreased slightly, which may be material to an analysis.

LONG-TERM CARE INSURANCE

Long-term care insurance provides members with reimbursement if the member needs home health care or nursing home care at some point. Premiums are set at issue and remain level over the lifetime of the member unless a rate increase occurs. Rate increases are rare and often frowned upon by regulatory authorities. Estimating claims costs for long-term care insurance requires three types of assumptions:

- *Transition Probabilities*. A transition probability represents the probability that a person will enter a nursing home or require home health care. Transition probabilities generally vary by age. The RV risk for transitions can be determined using the binomial or multinomial distributions. The projection risk must reflect not only how accurate the transition probabilities are today, but how they might change over time because of factors such as provider supply.
- *Continuance Tables*. A continuance table assigns values for the probability that the person would stay one day, two days and so on. For any given continuance table, the RV risk can be determined in a manner similar to that described in Section 3. That said, the projection risk must consider the fact that the shape of the continuance table may change in time.
- *Cost Per Service*. If the policy is based on a defined benefit, such as $500 per day in a nursing home, then minimal projection or RV risk is associated with costs. That will not be the case with other benefit designs.

DRUG DEVELOPMENT COSTS

Large pharmaceutical companies such as Pfizer and AstraZeneca often spend hundreds of millions of dollars developing a new drug without knowing if the drug will even work. Historically, companies have had considerable latitude in increasing prices over time. Under the Inflation Reduction Act passed in 2022,[31] however, the company must pay a rebate if a drug price increases higher than general inflation. This puts considerable pressure on determining the right launch price. The projection process must reflect factors such as potential alternative drugs, expected increases or decreases in the incidence and prevalence of the underlying conditions, and general inflation. The RV risk associated with a new drug should reflect the cost distribution by disease state.

INVESTMENTS

Risk theory is not a new concept in investment analytics. Much of the existing risk theory is based on the concept of an efficient market. The term "efficient market" implies that everything that needs to be considered in the price of a specific stock is already baked into the price. As a result, the expected change in price for the stock will be random. The size of the change, however, will depend on the volatility of the stock, which is often referred to as "beta." This concept was memorialized in the book *A Random Walk Down Wall Street*[32] and further explored using the variance-at-risk analytical technique.

Like the classical risk theory described above, these concepts provide a basis for the RV risk. A projection risk also exists, however. The most obvious example is that for short-term analytics the value of beta may be overstated or understated, resulting in a projection miss. For longer-term analytics, factors such as the general economy, competitors and other disruptors must be considered in the projection.

4.6 NON-INSURANCE APPLICATIONS

The basic principle behind TRA is that if a projection is based on an average, then the variation within the average needs to be considered in determining total risk. At some point this idea needs to be explored for non-insurance applications.

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Endnotes

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[1] Centers for Medicare and Medicaid Services. 2023. Historical National Health Expenditures, Table 1. *CMS.gov, https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/historical* (accessed Sept. 15, 2023).

[2] Actuarial Standards Board. March 2013. Introductory Actuarial Standard of Practice, Actuarial Standard of Practice No. 1. *actuarialstandardsboard.org, https://www.actuarialstandardsboard.org/asops/introductoryactuarialstandardpractice* (accessed Sept. 15, 2023).

[3] Casualty Actuarial Society, CAS Enterprise Risk Management Committee. 2003. Overview of Enterprise Risk Management. *casact.org, https://www.casact.org/sites/default/files/database/forum_03sforum_03sf099.pdf* (accessed Aug. 26, 2023).

[4] Barrett, Joan C. 2021. Medical Claims Cost Trends, in *Group Insurance,* 8th ed., edited by Daniel D. Skwire, chapter 35 (accessed Aug. 26, 2023). Actex Learning, Greenland NH.

[5] Wasserstein, Ron. 2010. George Box: A Model Statistician. *Significance, https://rss.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1740-9713.2010.00442.x* (accessed Aug. 26, 2023).

[6] Actuarial Standards Board. 2019. Actuarial Standard of Practice No. 56, Modeling. *actuarialstandardsboard.org, https://www.actuarialstandardsboard.org/asops/modeling-3/* (accessed Aug. 26, 2023).

[7] Mitchell, Emily M. February 2022. Concentration of Healthcare Expenditures and Selected Characteristics of High Spenders, U.S. Noninstituationalized Population, 2019. AHRQ Statistical Brief no. 540. *meps.ahrq.gov, https://meps.ahrq.gov/data_files/publications/st540/stat540.shtml?msclkid=48400ec0d13211ecbf44a86a0e73d4e6* (accessed Aug. 26, 2023).

[8] Health Care Cost Institute. 2023. Data. *healthcostinstitute.org, https://healthcostinstitute.org/data* (accessed Aug. 26, 2023).

[9] Berchick, Edward R., Emily Hood, and Jessica C. Barnett. 2018. Health Insurance Coverage in the United States: 2017. Current Population Reports, U.S. Census Bureau. *www.census.gov, https://www.census.gov/content/dam/Census/library/publications/2018/demo/p60-264.pdf* (accessed Aug. 26, 2023).

[10] Neuman, Tricia, and Marsha Gold. 2017. Medicare Advantage 2017 Spotlight: Enrollment Market Update. *kff.org, https://www.kff.org/medicare/issue-brief/medicare-advantage-2017-spotlight-enrollment-market-update/#:~:text=In%202017%2C%20one%20in%20three%20%2833%25%29%20Medicare%20beneficiaries,beneficiaries%2C%20or%208%20percent%2C%20between%202016%20and%202017* (accessed Aug. 26, 2023).

[11] Johnson, William, Niall Brennan, Sally Rodriguez, and John Hargraves. 2018. Consistently High Turnover in the Group of Top Health Care Spenders. *New England Journal of Medicine,* February 1. *healthcostinstitute.org, https://healthcostinstitute.org/hcci-originals-dropdown/all-hcci-reports/new-england-journal-of-medicine-consistently-high-turnover-in-the-group-of-top-health-care-spenders* (accessed Aug. 26, 2023).

[12] Yamamoto, Dale H. June 2013. Health Care Costs—From Birth to Death. Health Care Cost Institute Independent Report Series. Sponsored by the Society of Actuaries. *healthcostinstitute.org, https://healthcostinstitute.org/images/pdfs/Age-Curve-Study_0.pdf* (accessed Aug. 26, 2023).

[13] Downing, Douglas, and Jeffrey Clark. 2010. *Business Statistics*. 5th ed. (New York: Barron's).

[14] Ibid.

[15] Centers for Disease Control and Prevention. 2023. About Chronic Diseases. *cdc.gov, https://www.cdc.gov/chronicdisease/about/index.htm* (accessed Aug. 26, 2023).

[16] Buttorff, Christine, Teague Ruder, and Melissa Bauman. 2017. Multiple Chronic Conditions in the United States. RAND Corporation. *rand.org, https://www.rand.org/content/dam/rand/pubs/tools/TL200/TL221/RAND_TL221.pdf* (accessed Aug. 26, 2023).

[17] Mitchell, note 7 above.

[18] Claxton, Gary, Mathew Rae, and Larry Levitt. July 22, 2019. A Look at People Who Have Persistently High Spending on Health Care. *healthsystemtracker.org, https://www.healthsystemtracker.org/brief/a-look-at-people-who-have-persistently-high-spending-on-health-care* (accessed Aug. 26, 2023).

[19] March of Dimes Perinatal Data Center. 2011. Special Care Nursery Admissions. *kff.org, https://www.kff.org/wp-content/uploads/sites/2/2013/01/nicu_summary_final.pdf* (accessed Aug. 26, 2023).

[20] Mayo Clinic. 2023. Premature Birth. *mayoclinic.org, https://www.mayoclinic.org/diseases-conditions/premature-birth/symptoms-causes/syc-20376730* (accessed Aug. 26, 2023).

[21] Duncan, Ian, Tamim Ahmed, Henry Dove, and Terri Maxwell. 2019. Medicare Cost at End of Life. *American Journal of Hospice* 36, no. 8: 705–710. *https://journals.sagepub.com/doi/full/10.1177/1049909119836204* (accessed Aug. 26, 2023).

[22] Actuarial Standards Board, note 6 above.

[23] Ibid.

[24] Barrett, note 4 above.

[25] Ibid.

[26] Atkinson, David B. 2019. Credibility Applications for Life and Health Insurers and Pension Plans. Society of Actuaries. *soa.org, https://www.soa.org/globalassets/assets/files/resources/tables-calcs-tools/credibility-methods-life-health-pensions.pdf#:~:text=There%20are%20three%20major%20families%20of%20credibility%20methods,actuaries%20today%3A%20Limited%20Fluctuation%2C%20Greatest%20Accuracy%2C%20and%20Bayesian.* (accessed Oct. 16, 2023).

[27] Centers for Medicare and Medicaid Services, note 1 above.

[28] Health Care Payment and Learning Action Network. 2017. Alternative Payment Model APM Framework. *hcp-lan.org, https://hcp-lan.org/workproducts/apm-refresh-whitepaper-final.pdf*. (accessed October 16, 2023)

[29] Duncan, Ian. 2014. *Managing and Evaluating Healthcare Intervention Programs.* 2nd ed. ACTEX Publications, Winsted CT.

[30] Kim, Kyeonghee, and Marjorie A. Rosenberg. 2020. Determinants of Persistent High Utilizers in U.S. Adults Using Nationally Representative Data. *North American Actuarial Journal* 24, no. 1: 1–21. *https://www.tandfonline.com/doi/abs/10.1080/10920277.2019.1585880* (accessed Oct. 16, 2023).

[31] Cubanski, Juliette, Tricia Neuman, and Meredith Freed. 2023. Explaining the Prescription Drug Provisions in the Inflation Reduction Act. *kff.org, https://www.kff.org/medicare/issue-brief/explaining-the-prescription-drug-provisions-in-the-inflation-reduction-act* (accessed Oct. 16, 2023).

[32] Malkiel, Burton G. 2007. *A Random Walk Down Wall Street* (New York: W.W. Norton and Company).

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