Paper 160-2010

Physician Practice Pattern Variation

Using Data Mining and Predictive Modeling to Identify and Control Costly Treatment Patterns

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ABSTRACT

The Challenge:

A major provider of health insurance wanted to identify which physicians (in their network) were providing excessively costly services and treatments for a given health condition (upper respiratory infections) and develop a business process to influence practice patterns in such a way as to control costs.

The Solution:

Using an innovative fusion of analysis-of-variance and predictive modeling, “expected costs” were calculated for each physician, based on member health, condition(s) being treated, and physician demographics. This allowed for an automated process to compare actual costs to expected costs, and to “red flag” physicians.

The Outcome:

$10 million in annual cost-control opportunity identified for a single condition (upper respiratory infections).

Some Details:

The big breakthrough in this area was to devise an approach to model the expected costs associated with treating a given condition (upper respiratory infections). This discussion will cover the three main areas of this project (Data Summarization, Modeling, and Information Delivery) with a focus on an effective approach to turning analytical output into actionable business information.

INTRODUCTION

One day, Dr. Sue was visited by a patient of hers who has had repeated bouts of sinusitis. This patient has responded well to a particular antibiotic in the past. So, Dr. Sue tries that approach again, prescribing a round of inexpensive antibiotics. In fact, Dr. Sue has developed a pattern of treating such a condition with antibiotics.
Across town, on the same day, Dr. Bob is visited by a patient of his who has had repeated bouts of sinusitis. Dr. Bob decides it’s not only time to use the CAT scanner in his facility, but it is also time to refer this particular patient to an ear, nose, and throat specialist. Ultimately, his patient has surgery as part of the plan to address the chronic sinusitis. History has shown us that Dr. Bob has a pattern of using the CAT scanner in his office, as well as referring to specialists.

Drs. Sue and Bob have developed very different practice patterns for treating sinusitis. These practice patterns have very different cost structures. Even with evidence-based standards for treating such a condition, we still see tremendous variability in practice patterns for treating sinusitis.

Many health insurance providers, and other such organizations, are concerned with the ever-increasing costs of healthcare. Even after adjusting for population growth and shifts in age distribution, the cost of U.S. healthcare has grown at a significantly faster rate than could be explained by simple inflation. Most projections, such as that shown in Figure 1, show that this observed growth in healthcare costs will only continue.

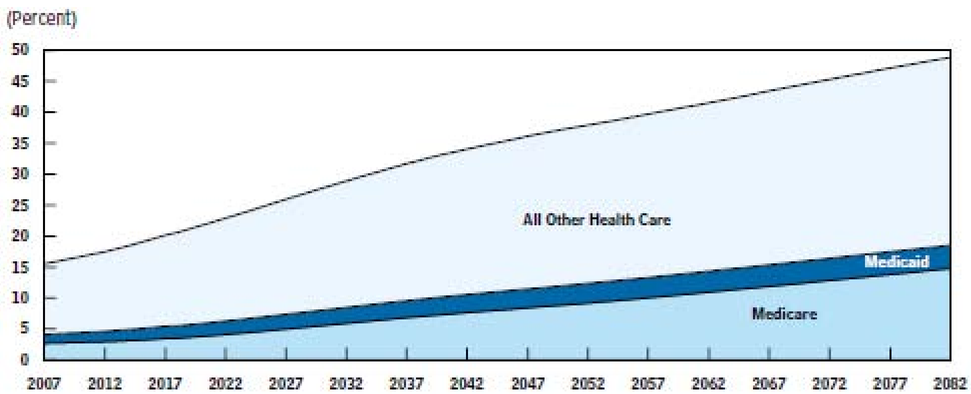

Figure 1: Projected Spending on Health Care as a Percentage of Gross Domestic Product. Source: U.S. Congressional Budget Office.

The purpose of this paper is to outline an analytic approach for quantifying excessive costs as caused by physicians’ practice pattern variation (PPPV), to understand the root causes of such variability, and to identify opportunities to reduce costly variability of treatments and services provided.

COST VARIANCE MODELING

The goal of reducing costs is certainly not unique to the healthcare industry. Whether costs are being generated by units manufactured, products sold, services provided, or patients treated, there is a challenge in determining the underlying drivers of costs. In order to understand how to reduce costs, in any industry, you must identify where the excessive costs are coming from.

But how should we define “excessive”?

Actual costs are easy to measure. And one might decide that identifying *excessive* costs is as simple as determining which units (or products or people) are generating the highest *actual* costs. In the healthcare industry, if you used such an approach and simply identified which physicians generated the highest dollar amount of insurance claims, there would be no notion of how much cost *should* they be generating. Given the mix of patients they treat, their location and the facilities they utilize, and the types of conditions in which they specialize, how much cost *should* they generate?

A key concept in the development of the Physician Practice Pattern Variation (PPPV) solution is the notion of determining *expected* costs. The approach to determining the expected costs is through “cost variance modeling.” Neither this terminology, nor the approach in general, is widely used. But this author has found it useful in various industries and for various analytic objectives.

Cost Variance Modeling is, in essence, a fusion of Outlier Detection, Statistical Process Control concepts, Predictive (or Explanatory) Modeling, and Analysis of Variance.

First, consider the concept of outlier detection. When developing a predictive model, perhaps through linear regression, it is often useful to determine if there are any anomalies in the data…any extreme values that could cause the regression algorithm to produce a nonrobust model. For developing a regression model, outliers are often removed from the input data. Figure 2 shows how one might use a residual analysis to visually spot an outlier.

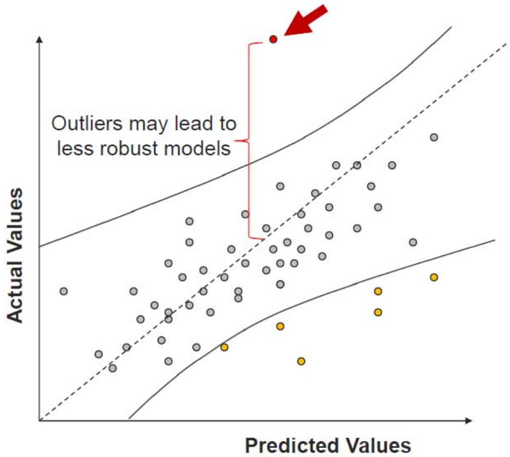

**Figure 2: Sample residual plot,
showing what appears to be an outlier.**

When an outlier is detected, for predictive modeling purposes, it is often “thrown out.” For Cost Variance Modeling, and specifically for Physician Practice Pattern Variation, we do not want to throw out the outliers. We want to determine what is causing the costly outliers. This is closely aligned with the concepts of quality control, or statistical process control. As depicted in Figure 3, in statistical process control, spotting outliers is just the beginning of determining their underlying causes, so as to systemically remove them from future occurrences.

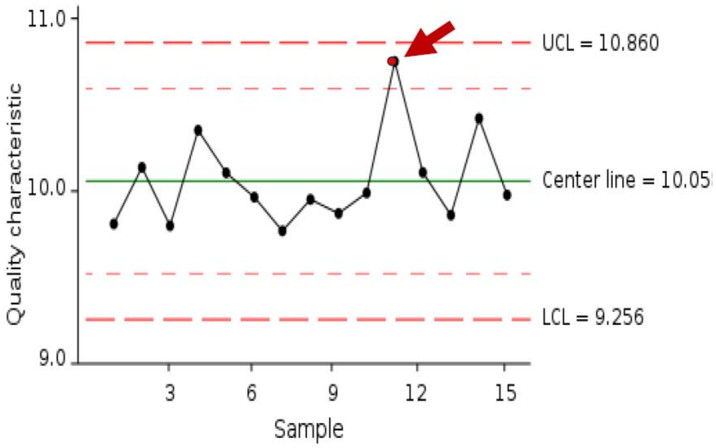

Figure 3: Sample control chart, showing what appears to be an out-of-control event.

For Physician Practice Pattern Variation, we want to identify the costly outliers, by determining which physicians are generating more than expected costs. Figure 4 shows, pictorially, how the relationship between expected costs and actual costs is used to establish which physicians are generating more than expected costs, which are generating less than expected costs, and which are within an acceptable zone of tolerance (in which actual costs are roughly equal to expected costs).

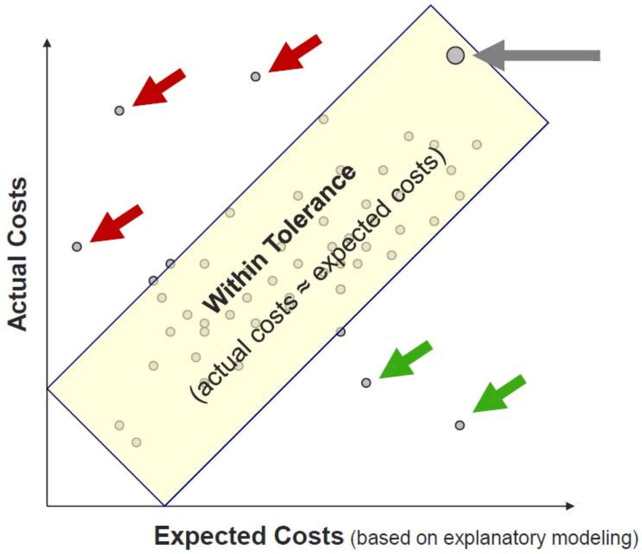

Figure 4: Comparison of actual and expected costs. Each observation (or dot) represents a physician.

If each dot in Figure 4 represents a particular physician, then those identified with red arrows are of particular interest, as those are the physicians generating significantly higher costs than expected.

In order to fully understand the relevance of the Cost Variance Modeling concept, we should pay close attention to the physician identified in Figure 4 by the *grey* arrow pointing to the large dot. This physician has the highest actual costs. However, this physician's expected costs are roughly equal to her actual costs, and are thus within the zone of tolerance. In other words, for this example depicted in Figure 4, our focus on where to remove costs would *not* focus on the physician who is generating the highest actual costs.

Before we can determine which physicians are generating higher than expected costs, we need a methodology for *calculating* expected costs.

MODELING EXPECTED COSTS

Modeling expected costs is a mixture of science and art, and determining what should be included in the equation can lead to a bit of a philosophical discussion. But as a starting point, let's establish the general form of any equation to be used for modeling expected costs. Regardless of the industry, the general form of the equation is:

expected cost = $a_1 * X_1 + a_2 * X_2 + a_3 * X_3 + \ldots + a_n * X_n$

where X_i is a measure of variable units for a particular cost-driving factor, and
a_i represents the cost per unit of X_i.

That's the scientific part…having an *equation* that quantifies an *expected* value. The *artistic* aspect is twofold:

1. The desired equation is *explanatory*, not predictive (more on this below).
2. Determining which cost-driving factors (X_i's) should and should *not* be included in the equation may lead to difficult, philosophical considerations.

First, let's discuss the difference between an explanatory model and a predictive model. For many modeling applications, the desire is to develop a predictive model. In such situations, the model is used to predict an outcome, given necessary inputs. For a predictive model, it is relatively straightforward to determine whether your model is "good" via a variety of goodness-of-fit statistics and the use of a holdout sample. If your predictive model accurately predicts the future on a holdout sample of data, and subsequently makes for accurate predictions upon implementation, then your predictive model is good.

However, the goal of modeling expected costs is primarily to determine "red flags" that have occurred in the past, and not necessarily to predict the future. The measure of "goodness" for an explanatory model designed to quantify historical expectations is not so well defined, thus the art form and thus the potential for philosophical considerations.

Before we can structure an equation to quantify the expected costs generated by physicians, it's essential that we thoroughly understand the implications of what we might choose to include, or not to include, in such an explanatory equation. To understand the question as to what should and what should not be included in the equation, let's first consider a simplified example from a hypothetical shipping company, known as ReadyShip.

ReadyShip's business is in providing ground transportation of boxed packages. ReadyShip employs 1,000 drivers, who essentially drive vans all day, picking up and delivering packages. They call their drivers "roadies." Each roadie generates cost in two fundamental ways—their hourly pay and the gas consumed while driving their routes.

One approach to modeling the expected costs for each roadie would be:

expected cost for roadie = $a_1 * X_1 + a_2 * X_2$

where X_1 is a measure of hours worked, and a_1 represents an hourly pay rate; and
X_2 is a measure of miles driven, and a_2 represents a cost per mile for gas.

Such an equation would probably be a very accurate predictive model; with given values for hours worked and miles driven, this equation would very accurately predict what the resulting costs would be.

However, we do not want to accurately predict the costs. We want to know how much cost each roadie *should have* generated. Should they have worked as many hours as they did? Some roadies may be wasting time by stopping at too many convenience stores. Should they have driven as many miles as they did? Some roadies may be choosing very inefficient driving routes and adding unnecessary mileage to their deliveries. In order to develop an explanatory model that tells us how much cost they should have generated, we may choose a very different set of inputs to the equation. For instance, we may want to measure each roadie's total number of stops, the average distance from the distribution center to each stop on their route, the number of packages they delivered, the average weight and size of each package, indicators for the number of deliveries to loading docks versus malls, etc.

The purpose of this example is to emphasize these points:

1. The goal is *not* to accurately predict costs. The goal is to determine expected costs.
2. Deciding what to include and what not to include in the equation requires a bit of art (coupled with knowledge of the business processes).
3. Deciding what to include in the development of the equation is not based on what *does* drive costs, but rather is based on what *should* drive costs.

In order to apply these points to the task of modeling expected costs for physicians, we can start by brainstorming all factors that do drive costs, but we ultimately need to decide what *should* drive costs. In the context of Physician Practice Pattern Variation, this exercise will take on different flavors, all depending on which health condition(s) we address. In order to focus this paper, we will consider only Upper Respiratory Infections (URI). For the purposes of this paper, we will consider 3 types of URI: otitis media, sinusitis, and tonsillitis.

A first pass at deciding what should be included in the modeling is as follows:

expected costs = f (# and types of URI episodes treated,
patients' overall health, mix of patient demographics,
physician's specialty and demographics)

Notice what is *not* included in the equation: there are no measures for the specific treatments and services used by the physician in treating the given condition. We could have included the number of episodes referred to radiology, the number of episodes treated with antibiotics, the number of episodes involving particular types of labs, etc. If we had, we would produce an equation that precisely predicted the resulting costs. But we must remain aware that the purpose is to determine the *expected* costs; and if we include measures for every single type of treatment and service used by a given physician, then we will have an accurate mode of *actual* costs, and not a good model for describing what *should* have happened.

As mentioned previously, this does open the door for difficult philosophical questions. For example, a fundamental question is whether or not to include measures for the number (and type) of surgeries performed. Clearly, if a patient goes to surgery for the treatment of an upper respiratory infection, they will incur much higher costs than a patient who is treated with a simple round of antibiotics. If you choose to include measures for surgeries in the equation, then you are deciding that surgeries are expected whenever a physician decides to use surgery as part of their practice pattern. If you decide to omit measures for surgeries from the equation, then you are deciding that surgeries are an optional procedure. This sort of decision represents the biggest philosophical question to tackle prior to developing the equation, and it requires input from medical professionals.

It is this author's opinion that measures for surgery should be included in the equation to quantify expected costs. If not, the equation would need to include a vast array of medical history data, on each patient, as a proxy for determining whether surgery is justified. Certainly the equation should include some measures of patient health, but probably not so much as to completely explain whether surgery was necessary (or expected). Of course, the premise is not that every decision the physician makes is perfect. If that were the case, there would be no reason to model their expected costs in the first place.

Quick sidebar: When we speak of the physician, this is not necessarily the *treating* physician. We may want to model for the *responsible* physician. When grouping claims into episodes, it is possible to identify a responsible physician and to track all cost incurred for the episode across all physicians providing treatments.

If we decide to include surgeries as part of the expected cost calculation, then our second pass at the general form of the modeling is as follows:

expected costs = f (# episodes otitis media with *major* surgery treated,
episodes otitis media with *minor* surgery treated,
episodes otitis media with *no* surgery treated,
episodes sinusitis *with* surgery treated,
episodes sinusitis *without* surgery treated,
episodes tonsillitis *with* surgery treated,
episodes tonsillitis *without* surgery treated,
patients' overall health, mix of patient demographics,
physician's specialty and demographics)

If we structure the data appropriately, we can formulate the equation so as to have all coefficients be a cost-per-episode. For example, consider the following equation:

Parameter	Annual Cost per Episode		Parameter	Annual Cost per Episode
Intercept	$14.87		Board Certified = Yes	$13.31
Otitis Media w/o surgery	$71.14		geography = A	$100.28
Otitis Media w/ minor surgery	$1,288.54		geography = B	$27.27
Otitis Media w/ major surgery	$2,655.17		geography = C	$10.09
Sinusitis w/o surgery	$249.17		geography = X	$3.15
Sinusitis w/ surgery	$4,927.00		geography = Y	($5.27)
Tonsilitis w/o surgery	$50.94		geography = Z	($7.81)
Tonsilitis w/ surgery	$2,059.70		License yrs (cost per year per episode)	($0.58)
Age 5-18	$53.92		Specialty = EmergencyMed	$236.00
Age 19-30	($12.55)		Specialty = ENT	$145.28
Age 31+	($84.22)		Specialty = Pediatrics	$31.99
total patient-health-index-squared	$72.45		Specialty = OTHER	$125.77

Figure 5: Sample equation for calculating annual costs for physicians treating upper respiratory infections (URI).

It should be noted that this is a sample equation and should be used only as a guide to developing such an equation. Though these coefficients are realistic, they are not intended to be used by the reader for the calculation of expected URI costs.

The underlying data used to generate this equation was a summary of metrics, per physician. The summarization of the data was structured so as to provide each metric as a summary of episodes. In the equation above, the terms in the right-hand column represent demographic information for the physician. Consider the indicator for board certification. The metric used is not a simple indicator as to whether the physician was board certified. Rather, the data was structured so that the board certification indicator was weighted by the number of episodes treated. Thus, the coefficient of $13.31 suggests that if a physician is board certified, their expected annual costs (for treating URI episodes) will be $13.31 greater, per episode, than for a peer who is not board certified.

To see how this equation is applied, consider the following data, which represents the metrics collected for a given physician:

Parameter	Episode Count (weighted)		Parameter	Episode Count (weighted)
Intercept	n/a		Board Certified = Yes	207
Otitis Media w/o surgery	64		geography = A	0
Otitis Media w/ minor surgery	34		geography = B	0
Otitis Media w/ major surgery	1		geography = C	0
Sinusitis w/o surgery	27		geography = X	0
Sinusitis w/ surgery	9		geography = Y	207
Tonsilitis w/o surgery	29		geography = Z	0
Tonsilitis w/ surgery	43		License yrs (cost per year per episode)	2,070
Age 5-18	83		Specialty = EmergencyMed	0
Age 19-30	56		Specialty = ENT	207
Age 31+	68		Specialty = Pediatrics	0
total patient-health-index-squared	912.9		Specialty = OTHER	0

Figure 6: Sample metrics collected for a given physician treating upper respiratory infections (URI).

We can see in Figure 6 that this particular physician treated 207 URI episodes, broken down by type of URI (e.g. 64 otitis media episodes treated without surgery). This physician treated all types of URI, as well as all age ranges, is board certified, practices in geography Y, and is an ENT (ear, nose, and throat specialist). Further, there is a measure of patient health risk, summed across all episodes. The raw health index used, for each patient, has a range of 1 to 5. In calculating the overall health risk, as used in the equation, the health index is squared, and summed across all episodes. Thus, the value of 912.9 reflects an average health risk of 2.1 (the square root of 912.9/207). To understand how the data is used, we must keep in mind that the data is structured so as to be a count of episodes, or a metric weighted by the count of episodes. For example, notice that the metrics associated with patients' ages sum to 207 (the total episode count). Also, notice that the metric for board certification is equal to the total episode count. This physician was board certified for each episode treated, and thus the impact of board certification (on total cost) is multiplied by the number of episodes. Finally, the value of 2070 for the "License yrs" metric indicates that this physician has been licensed for 10 years (10*207=2070); and the coefficient represents a cost per episode per year licensed.

In order to calculate the total expected annual costs for this physician, represented in Figure 6, we multiply those quantities by the coefficients found in Figure 5. Doing so, we see the impact of each factor on the expected annual costs (rounded to whole dollars):

Parameter	Expected Annual Cost		Parameter	Expected Annual Cost
Intercept	$15		Board Certified = Yes	$2,754
Otitis Media w/o surgery	$4,553		geography = A	$0
Otitis Media w/ minor surgery	$43,810		geography = B	$0
Otitis Media w/ major surgery	$2,655		geography = C	$0
Sinusitis w/o surgery	$6,728		geography = X	$0
Sinusitis w/ surgery	$44,343		geography = Y	($1,092)
Tonsilitis w/o surgery	$1,477		geography = Z	$0
Tonsilitis w/ surgery	$88,567		License yrs (cost per year per episode)	($1,201)
Age 5-18	$4,476		Specialty = EmergencyMed	$0
Age 19-30	($703)		Specialty = ENT	$30,073
Age 31+	($5,727)		Specialty = Pediatrics	$0
total patient-health-index-squared	$66,134		Specialty = OTHER	$0

Figure 7: Expected costs, by cost-driving factor, for a particular physician treating upper respiratory infections (URI).

The multivariate equation in Figure 5, multiplied by the relevant metrics found in Figure 6, gives us the dollar impact of each factor, as seen in Figure 7. Summing the costs across each factor, we determine that this physician's expected cost, for treating these 207 episodes of URI, is equal to $286,863. A different physician treating the same mix of episodes, but practicing in a different geography, with a different patient mix, and a different specialty, would have different expected costs. Similarly, a physician operating in the same geography, with a similar patient mix, practicing the same specialty, but with a different mix of URI episodes (e.g. all tonsillitis but no sinusitis) would have a different value of expected costs.

After calculating the expected cost of $286,863 for this particular physician (let's say this is for Dr. Bob), the next step is to compare that to the actual costs incurred by Dr. Bob. If the actual costs are significantly higher than expected, then we would subsequently "red flag" this physician, and want to understand what specific practice patterns led to the higher costs. We will discuss that process more in the Information Delivery section below.

Before we take a look at the format of the Information Delivery, let's take a step back and evaluate precisely what data is needed to develop the expected cost model.

DATA SUMMARIZATION

Once we have the equation generally formulated, we can design an input data set for such a modeling exercise. In order to formulate the equation, we need to start with a list of *possible* drivers of cost. As with any modeling exercise, we don't know what final form the equation will take. Going back to the general form of the equation for URI, in order to design the appropriate input data set, we need to add more detail to these terms:

patients' overall health,
mix of patient demographics,
physician's specialty and demographics.

Not all desired data elements will be available, but the following lists many of the desired metrics, specific to developing the expected cost model for physicians treating URI.

patients' overall health:

- presence of comorbidities, such as indicators for heart disease, cancer, etc.
- count of past URI episodes
- recent body weight change and blood pressure readings
- indication for being a smoker
- participation wellness programs (e.g. indicator for smoking-cessation program)

patient demographics:

- age
- gender
- marital status

physician's specialty and demographics:

- specialty
- years since obtaining medical license
- geographic location
- indicator for board certification

There are two very important considerations while collecting, and summarizing, such data:

1. Because we are modeling expected costs *at the physician level*, all data needs to be summarized to the physician level.
2. Because we want the resulting equation to provide cost-per-episode coefficients, all metrics should be reflected as a count of episodes, or a metric weighted by a count of episodes.

In order to address the first consideration, the physician should be thought of as a key by which all data is summarized and joined. For instance, when collecting metrics on each patient's count of past URI episodes, such a metric may be independent of any single physician, but ultimately this patient-specific metric would be summarized to the physician level. Such a linkage may be via a physician_ID being associated with an episode_key, which may in turn be associated with a given patient.

In order to address the second consideration above, think of the episode as the original layer of detail. Each episode would be associated with a given patient and a given physician. Suppose that one of the metrics you want to summarize is patient age, in the form of labeling age ranges (for instance, 5-18, 19-30, and 31+). Each episode detail could receive a binary (0/1) indicator for whether the patient was age 5-18, captured in a variable called Age_5_18. Then, when summarizing Age_5_18 from episode detail to the physician level, the resulting metric would be a count of all episodes associated with patients of age 5 to 18. And the coefficient of the Age_5_18 metric would represent the incremental expected cost (positive or negative) for each episode involving a patient of that age range.

Going back to the discussion on modeling expected costs, instead of predicting actual costs, we must keep in mind that we do not want to include every scrap of information about each episode. For instance, from medical claims data, we could certainly identify which episodes were treated with expensive anti-inflammatory drugs, which involved expensive labs and radiology, etc. However, as stated previously, if we were to summarize all such information to the physician level, and use that in our equation, the result would not be a model of *expected* costs.

Our discussion on data, thus far, has focused on the data needed to develop the expected-cost-model. However, there is another important goal in summarizing the data—information delivery. Suppose that we have developed the expected-cost-model and determined that Dr. Bob's *expected* cost (for last year, for treating URI) was $286,863. Further, suppose that Dr. Bob's *actual* cost totaled $426,722. There is a positive delta, between actual and expected cost, of nearly $140,000 for Dr. Bob. What the model does *not* tell us is precisely what caused that delta. In order to determine that, we need an effective tool for decomposing that $140,000 delta into the specific services and treatments, used by Dr. Bob, that caused the excess.

Structuring the input data to allow for an investigation of what caused the excessive costs requires that the episode detail is maintained. Thus, for the purposes of modeling expected costs, the episode detail is summarized to the physician level. However, for the purposes of investigating the cause of the excessive costs, as is depicted in the Information Delivery section of this paper, there is need to drill down into the specific services and treatments. Because of the uniqueness of each company's data, the intent of this paper is *not* to identify specific data elements and tables involved in such a process. Rather, the reader should be able to take the information from this paper and use it to identify the relevant data elements and sources found within your company.

INFORMATION DELIVERY

The output from the expected-cost-model is a determination for which physicians are generating actual costs that are roughly equal to expected costs, and those who are generating actual costs that are unusually higher or lower than expected costs. In order to transform such output into actionable business information, we first need to establish a rule for "red flagging" physicians. As a starting point, we can calculate the delta (equal to actual costs minus expected costs) for each physician. There will be those physicians with significantly higher than expected costs, on a percentage basis. For example, if Dr. Sue has an expected cost of $1,000, and her actual cost generated was $10,000, then Dr. Sue has generated 10-times the cost you would expect. However, Dr. Sue may not be one we'd like to investigate, simply because her annual actual costs are relatively low. If we want to devise a strategy to remove costs from the business, we'd have to investigate hundreds or thousands of physicians like Dr. Sue.

Our focus should be on identifying the physicians with the largest opportunity, measured in dollars. After calculating the delta for each physician, we can "flag" the top 5% of physicians in terms of positive deltas. Experience shows that a vast majority of the cost-reduction opportunity will be found by focusing on this limited number of physicians. In our example, Dr. Bob would be among the 5% we'd want to investigate, because there is nearly $140,000 of cost-reduction opportunity for this single physician.

One approach would be to simply make Dr. Bob aware of his $140,000 delta, and trust that he would correct his practice patterns if such a correction is warranted. However, a much better approach is to generate actionable output that highlights precisely which treatments and services are causing the delta. To do this, let's start with the end in mind. Suppose that we have determined, through a bit of lucky ad hoc analysis, the following information about Dr. Bob:

- There is a particular CPT code, found on claims associated with otitis media episodes treated by this physician, which occurs far more frequently than expected (when comparing his results to his peers of the same specialty).

Suppose that we saw a particular "layer 4" report (where layer 4 refers to the lowest level of detail we can analyze in terms of particular treatments provided), as shown in Figure 8:

MD: Bob Specialty: ENT
Type of URI: Otitis Media, w/o surgery
episode count = 64
Service: Injections, Subcategory: Injections Specialist Other
Layer 4 Code Type: CPT Full

Layer 4 Code	Layer 4 Item Description	Peer Group Utilization	Provider Utilization	Peer Group Cost per Episode	Provider Cost per Episode
95165	**PROFESSIONAL SERVICES SUPERVISION & PROV**	**6.26%**	**31.25%**	**$540.85**	**$678.11**
95120	IMMUNOTHERAPY,ALLERGENIC EXTRACT,SINGLE	0.58%	0.00%	$67.56	$0.00
95125	IMMUNOTHERAPY,ALLERGENIC EXTRACT,MULTIPL	0.58%	0.00%	$229.71	$0.00
9516559	PROFESSIONAL SERVICES SUPERVISION & PROV	0.02%	0.00%	$13.00	$0.00
95170	ALLERGEN IMMUNOTHERAPY SERVICES	0.02%	0.00%	$7.50	$0.00

Figure 8: Sample "layer 4" report showing physician over-utilization, for a particular type of service associated with URI.

We know that Dr. Bob treated 64 episodes of otitis media, without surgery, last year. If he utilized CPT code 95165 as often as his peers, then he would have used this CPT code on only 4 episodes. However, Dr. Bob charged this particular CPT code (95165) on 20 episodes. Perhaps this is a relevant finding, and perhaps this information should be shared with Dr. Bob.

But first, we need to develop a systematic plan for how to uncover all such interesting results. The report shown in Figure 8 is for a very small subset of possible treatments/services that could be provided by Dr. Bob. Across all the types of URI episodes that Dr. Bob treats, there are hundreds of CPT codes, hundreds of drug codes, dozens of surgery code, etc. Given the vast number of detailed codes, associated with Dr. Bob's practice patterns for treating URI, if we were to generate all such possible reports, there would be a large number of reports to view—just for this single physician. If we were to generate all such reports for *all* our practicing physicians treating URI, we would have a mountain of information to sift through. In fact, suppose that we have 5,000 physicians treating URI, and we want to produce a report that shows detailed treatment patterns (exemplified in Figure 8), for each combination of physician, type of URI (tonsillitis with surgery, tonsillitis without surgery, etc), and type of service (imaging, lab, pharmaceuticals, etc). This would result in approximately 250,000 such reports. Producing all such reports is not efficient. Sifting through such reports in an ad hoc manner is not effective.

In order to take the results of the expected-cost modeling and produce actionable information, we need an *automated* approach to generating *only those reports that are relevant*; only those reports that identify a practice pattern leading to higher than expected costs.

It exceeds the scope of this paper to detail exactly how such an automated reporting system can be built in SAS®, but the following depicts an example of automated reports generated within SAS® Enterprise Guide®. In the following automated drill-down, only the relevant reports are generated, and the areas of focus are automatically highlighted to identify where higher than expected costs are found.

For our drill-down example, let's introduce another physician, Dr. Al, the Allergist. We've used our equation to determine that Dr. Al has generated nearly $30,000 of excessive costs (difference between actual and expected), in total. Dr. Al treats several types of URI, and in our first layer of drill-down, we want to determine which type(s) of URI are of most interest.

We know that Dr. Al treats both sinusitis and otitis media. Using an equation structured like that shown in Figure 5, we can simply plug in the sinusitis-specific metrics for Dr. Al. In other words, even though the equation is developed for the physician overall, we can collect metrics such as the age-related metrics, the health-risk-related metrics, and so on, for only the sinusitis episodes, and calculate Dr. Al's expected costs for treating 103 episodes of sinusitis. Similarly, we can do the same for the otitis media episodes and determine that the primary cause of Dr. Al's $30,000 delta is a $25,000 delta for sinusitis alone.

For reference, we will call the physician level of reporting "Layer 0," and the type of URI (i.e. sinusitis with surgery, sinusitis without surgery, etc) a "Layer 1" drill-down. Just as we can automate the identification of the top 5% of physicians in terms of cost delta (difference from expected), we can also automate the identification of which types of URI are causing the excessive costs, for each physician, by aggregating the metrics to the physician-and-type-of-URI level and running those through the expected cost equation. In order to drill down further, we need to define further layers of drill-down, as follows:

Layer 0 = physician (e.g. Dr. Al).

Layer 1 = type of URI, by physician (e.g. sinusitis without surgery, for Dr. Al).

Layer 2 = type of service, by type-of-URI, by physician.
Likely types of service include consultation, imaging, injections, lab, pharmaceuticals, and surgery.

Layer 3 = subcategory of service, by type of service, by type of URI, by physician.
Subcategory of services would be a mapping of individual CPTs, drug codes, surgery codes, etc.,.into categories that provide insight at a layer of detail below the type of service. Specifics for such a mapping are at the discretion of the company implementing this approach. For example, consider these subcategories for type of service = Injections: allergens, antibiotics, vaccines, steroids, etc.

Layer 4 = individual CPT codes, drug codes, and surgery codes, by subcategory of service, by type of service, by physician.

As mentioned previously, a drill-down form Layer 0 to Layer 1 (from physician to type of URI) can be automated by quantifying expected costs for each type of URI (for a given physician) from the expected cost equation, where the inputs are metrics collected for a specific type of URI (e.g. based on only *sinusitis without surgery* episodes).

In order to drill down to Layer 2, we will report key metrics for each type of service, *only* for those Layer 1 results that have been "red flagged." For Dr. Al, the Layer 2 report is below:

MD: Albert   Specialty: Allergy
Type of URI: Sinusitis, w/o surgery
episode count =   103

Type of Service	Peer Group Utilization	Provider Utilization	Peer Group Cost per Episode	Provider Cost per Episode
Consultation	17.2%	28.2%	$213	$231
Imaging	9.5%	12.6%	$377	$394
Injections	**32.6%**	**44.7%**	**$586**	**$973**
Lab	12.4%	11.7%	$81	$44
MedCare	75.9%	85.4%	$253	$322
Other	4.0%	1.9%	$477	$851
Pharma	67.7%	72.8%	$229	$190
Surgeries	2.9%	5.8%	$214	$249

Figure 9: Sample "layer 2" report showing physician over-utilization. "Peer Group" can be defined as Specialty.

It should be noted that the report depicted in Figure 9 is an automated report generated with SAS and is not a manually formatted report. This automated process includes the highlighting of Injections, for this particular example. This begs the question, "What is the logic for highlighting this one particular row, Injections?" Because our expected cost model was not structured to model the expected costs for each type of service, nor for any level of detail below Level 1, we need some business rules to determine which Layer 2 result(s) should be flagged. In order to determine which types of service should be flagged, we will allocate the delta (that we calculated at Level 1) to each type of service, and determine which types of service account for a majority of the delta.

The logic for this "allocated delta" is as follows:

1. Calculate an approximate-expected-cost, abbreviated "Approx EC."
   Approx EC = physician's episode count * peer group utilization * peer group cost per episode
2. Calculate an interim delta (interim value of actual minus expected costs).
   interim delta = actual cost for type of service – Approx EC for type of service
3. Allocate the actual delta (for the given type of URI, for the physician) across types of service, as a percent of interim delta. This approach will produce a delta value, by type of service that will sum to the delta calculated at the type-of-URI level.

Looking at the Layer 2 report in Figure 9, we see that Dr. Al utilized Injections for 44.7% of the 103 episodes of *sinusitis without surgery* that he treated, while his peers (other allergists) utilized Injections for only 32.6% of *sinusitis without surgery* episodes. Further, we see that Dr. Al has a significantly higher cost per episode for Injections, as compared to his peers. However, it was neither a comparison of utilization nor of cost per episode that led to Injections being highlighted for Dr. Al. Rather, the Injections type of service was flagged as a result of a behind-the-scenes calculation for the allocated delta.

A similar approach of allocating the delta (taking the delta allocated to a Layer 2 and further allocating to the next level of detail), allows us to generate a Layer 3 report that shows more detail below Injections:

Subcategory of Service	Peer Group Utilization	Provider Utilization	Peer Group Cost per Episode	Provider Cost per Episode
Inj_Allergen_Immuno	27.3%	43.7%	$281	$387
Inj_Antibiotics	0.3%	0.0%	$74	$0
Inj_Immuno_Vaccine	0.2%	0.0%	$9	$0
Inj_Specialist_Other	**26.4%**	**42.7%**	**$430**	**$621**
Inj_Steroids	2.5%	1.0%	$10	$12
Inj_Undefined	0.0%	0.0%	$205	$0

Figure 10: Sample "layer 3" report showing physician over-utilization. Subcategories are defined roll-ups of CPT codes.

And similarly for Layer 4:

Layer 4 Code	Layer 4 Item Description	Peer Group Utilization	Provider Utilization	Peer Group Cost per Episode	Provider Cost per Episode
95165	**PROFESSIONAL SERVICES SUPERVISION & PROV**	**26.27%**	**42.72%**	**$427.15**	**$611.19**
9516559	**PROFESSIONAL SERVICES SUPERVISION & PROV**	**0.50%**	**10.68%**	**$46.17**	**$39.45**
95125	IMMUNOTHERAPY,ALLERGENIC EXTRACT,MULTIPL	0.21%	0.00%	$145.50	$0.00
95170	ALLERGEN IMMUNOTHERAPY SERVICES	0.21%	0.00%	$268.90	$0.00
95144	PROFESSIONAL SERVICES SUPERVISION & PROV	0.04%	0.00%	$11.00	$0.00
9516576	PROFESSIONAL SERVICES SUPERVISION & PROV	0.04%	0.00%	$260.00	$0.00

**Figure 11: Sample "layer 4" report showing physician over-utilization.
Layer 4 codes can be CPT, drug, or surgery codes, as appropriate.**

We see in this Layer 4 report that Dr. Al has utilized a particular CPT code (95165) much more frequently than did his peers. Further, this is a fairly expensive treatment, as seen in the cost per episode numbers for both the peer group and for Dr. Al. Though the information found in this paper has been anonymized, the results are real. In fact, upon implementation of this layered reporting system, based on the expected cost modeling, it was found that many of the allergists who were red-flagged had a portion of their excessive costs traced to apparent over-utilization of CPT code 95165. This particular finding is but one example of the insights to be gained by implementing a comprehensive Physician Practice Pattern Variation detection methodology, as described in this paper. This particular finding of the over-utilization of CPT code 95165 was without any prior knowledge (by the author) that such an issue might exist. After finding this recurring issue among allergists, the author of this paper did a bit of Internet research on this particular CPT code. The results of that Internet search, which could be easily repeated by the reader of this paper, were quite interesting! It seems that improper billing of this particular CPT code has been of great interest within the medical community.

CONCLUSION

With the methodology described in this paper, *all* practice patterns generating excessive costs can be identified and quantified.

And though this methodology was not developed with the intent of identifying *fraudulent* patterns of claims, this methodology has the potential for doing just that, as the practice patterns identified may not simply be inefficiencies.

It should be noted that any efforts to reduce costs should be done with an eye on treatment outcomes. The approach described in this paper does not tell us which treatments are most effective at curing disease or increasing good health. However, the approach described herein could certainly be expanded to include patient outcomes. Just as we can use this approach to model expected costs and analyze the practice patterns driving excessive costs, we could also use this approach to model expected health outcomes and analyze the practice patterns driving positive health outcomes.

Ultimately, quantifying and identifying the causes of excessive costs (as described herein), coupled with an analysis on health outcomes, could assist in developing standards-of-care for a variety of health conditions lacking such. If Physician Practice Pattern Variation methodology were to become widespread, it could provide a significant contribution to addressing the ongoing rise in healthcare costs.

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