Risk adjustment for pediatric populations

Howard Kahn, FSA, MAAA
Rob Parke, FIA, ASA, MAAA
Rong Yi, PhD

The use of risk adjustment in provider reimbursement arrangements has increased as alternative payment arrangements are becoming more widespread in health insurance. Risk adjustment has been used by Medicare Advantage and managed Medicaid programs to reimburse health plans for the unique risks and populations in their care. More recently, as carriers have transferred utilization risk to providers through alternative payment arrangements such as global budgets and bundled payments, risk adjustment has been used to reflect a provider's patient's severity. Also, under the Patient Protection and Affordable Care Act (ACA), beginning in 2014 risk adjustment will be used to transfer payments among all fully insured individual and small group plans.

However, many commercial risk adjustment methodologies applied were developed using a standard population representing a combination of adults and children. Adults comprise a larger proportion of the average population, and as a consequence, the disease states recognized in these methodologies were optimized with greater emphasis on adults. Because a chosen risk adjustment methodology should reflect the characteristics of the underlying patient population, organizations such as children's hospitals, pediatric provider groups, and health plans that enroll a large proportion of children have begun to question these standard risk adjustment models. These groups argue that there are fundamental differences in clinical profiles, patient mix, treatment options, and patient management needs between the pediatric population and the general population.

Risk adjustment is commonly used to recognize the relationship between the cost of delivering care and patient severity in order to redistribute the total amount of available funds among groups by relative risk scores.

In this paper, we compare results from a model we optimized for a pediatric population with a control model we developed for a standard population. This model is similar to many commercially available versions developed from the open source hierarchical condition categories (HCC) system.[1]

Risk adjustment modeling background

We begin by describing the construction of a typical HCC risk adjustment model.

A general risk adjustment formula for **n** defined conditions is represented as:

$$Y = I + C_1X_1 + C_2X_2 + \ldots C_iX_i + \ldots + C_nX_n$$

where Y = risk-adjusted expected claims cost (or risk score) for member **x**

I = intercept equivalent to the minimum cost (or risk score) assigned to a member

C_i = coefficient (risk weight) for the i^{th} clinical classification

X_i = member's value for the i^{th} clinical classification, such as asthma, diabetes, COPD, etc.

The first step in creating a risk adjustment model is to determine the number and definitions of the clinical classifications required. These classifications can represent any driver of healthcare cost found in claims data, but typically represent a collection of diagnoses and member demographics.[2] Careful consideration should be given to creating the clinical classifications, as they must have clinical face validity, not be so specific that they lose statistical credibility, be robust to coding pattern differences, and accurately predict average costs for all members in the population.

1 The HCCs are used in Medicare Advantage and Part D plans, in the federally administered risk-adjustment model for commercial individual and small groups starting in 2014, and in several states' Medicaid and subsidized insurance programs. The HCCs used in all of these systems have not been calibrated for a pediatric population.

2 There are also pharmacy-based risk adjustment models, which are typically used when the quality of medical diagnosis coding is questionable, e.g., due to capitation.

For example, a very simple risk adjustment formula might consist of only two classifications: age and diabetes. The formula is then represented as:

$$Y = I + C_{diabetes}X_{diabetes} + \sum_{i \in Age} C_iX_i$$

where $X_{diabetes}$ = 1 if the member has diabetes, 0 if the member does not (as defined by a set of ICD-9 diagnosis codes)

X_i = 1 if the member's age equals i, 0 otherwise

Statistical techniques are then used to estimate the value of the classification coefficients (risk weights). The resulting formula for a 40-year-old could be:

$$Y = \$100 + \$50X_{40} + \$2{,}000X_{diabetes}$$

This risk adjustment formula would then predict that a 40-year-old member who has diabetes would cost $2,150 for the year. However, a 40-year-old member who does not have diabetes is predicted to incur only $150 for the year, because that is the value of the age component (CageXage) added to the intercept ($100) in the formula. The intercept and risk weights (the resulting costs for each of the classifications, 50 and 2,000 in this example) are important aspects of the risk adjustment model, along with the definitions of the classifications. For instance, a refinement to the above simple model could be that diabetes is split into Type I and Type II diabetes, with and without complications.

Existing risk adjustment methodologies have been developed and used on populations that include a mix of adults and children. Does this type of methodology accurately capture the different characteristics of a pediatric-only population?

Is there a better alternative?

Adjustments to the general risk adjustment model

Before applying an existing risk adjustment model to a specific population, special consideration must be taken to ensure the model is a good fit. There are many reasons why a risk adjustment model would need to be adjusted:

1. **Unique population** – nuances about the population included in the claims data used to develop the risk weights.
2. **Unique contract** – the claims data does not represent the total cost of care but rather a component of the total (e.g., mental health and behavioral health carve-outs).
3. **Secular changes** – the risk weights were developed using data from a few years back and need to be updated to reflect current practice and treatment patterns.
4. **Coding convention changes** – starting in October 2014, diagnosis coding will be converted to ICD-10-CM. Both the classifications and the risk weights will need to be revised and updated. Classifications need to be ICD-10 ready before the official conversion date. Risk weights recalibrated on ICD-10 claims data will need to wait until an adequate volume of claims is available.

In this paper, we explore the consequences of item 1 above by measuring the effectiveness of a standard risk adjustment model on pediatric-only populations. To this end, we built a control model for a standard commercial population from the Truven Health Analytics MarketScan®[3] database. We limited our focus to New England States[4] and developed a concurrent[5] risk adjustment model with 184 disease classifications based on the HCC system. We note that this model is not a Milliman Advanced Risk Adjusters™ (MARA) risk adjustment model, but instead a control model for this specific analysis.[6]

The R-squared value[7] in our control model is 58% on the standard population. This is very similar to the reported R-squared values for many commercially available concurrent risk adjusters.[8] However, if we remove the adults from this population, our model's R-squared reduces significantly to 45% because the model's disease classifications and coefficients were optimized for a population that includes both adults and children.

3 Truven Health Analytics MarketScan® is a large and nationally representative commercial claims database. It is used to develop risk adjustment tools by many vendors of commercial risk adjustment tools.

4 We only used claims in New England states–Maine, Massachusetts, Connecticut, New Hampshire, Rhode Island, and Vermont–for model development.

5 A concurrent model uses the current year's data to risk adjust total cost of care within the year. We chose to develop a concurrent model because many recent global risk contracts retrospectively use risk adjustment at settlement.

6 For more information, go to http://us.milliman.com/Solutions/Products/Milliman-Advanced-Risk-Adjusters.

7 The R-squared statistic measures the amount of variability a model is capable of explaining in a population and is often used to evaluate the effectiveness of a risk adjustment model. A more accurate model results in a higher R-squared value.

8 See TABLE IV.7 of the 2007 SOA risk adjuster comparison study: www.soa.org/files/research/projects/risk-assessmentc.pdf.

Pediatric risk adjustment model

To improve the control model's R-squared of 45% for pediatric-only populations, we developed a pediatric-only model. We achieved this result through an iterative process using only the pediatric population included in our MarketScan database sample.

The detailed work flow of the model development process is summarized below:

1. We began the modeling at the DxGroup level that underlies the HCCs. There are 784 DxGroups in the original HCC classification system.

2. We modeled DxGroups with more than 30 patients separately and left those with fewer than 30 patients in their original HCCs.

3. We created two-way and three-way disease interactions for inclusion in the model (e.g., diabetes and chronic obstructive pulmonary disorder [COPD] would be included as an additional explanatory variable, in addition to diabetes alone and COPD alone). We calculated the sample size of each and retained only those that had at least 30 patients in a cell.

4. We regrouped DxGroups and disease interaction terms with statistically insignificant coefficients (at a 5% significance threshold) with the other small-cell DxGroups in the same HCC and recalculated their coefficients (risk weights).

5. We reset the coefficients of DxGroups and disease interaction terms with statistically significant but negative coefficients to zero. Negative coefficients often imply a confounding variable; if left in the model, they will produce spurious relationships among conditions. From a payment perspective, negative coefficients result in reduction in payment for diagnosing or treating a condition, which does not have face validity either.

6. We repeated steps (4) and (5) until all variables left in the model had statistically significant and non-negative coefficients. This resulted in 570 DxGroups/HCC categories.

By way of an example, the control model has a category called "other infectious diseases." Using the control model, we would only have one risk weight associated for all diseases falling under this category. However, in the pediatric model we refined this classification by splitting out "other bacterial infections," "bacterial infection in other diseases," "other viral infections," "other infections," "Lyme disease," and "bacteremia." Table 1 summarizes the risk weights for the general HCC category "other infectious diseases" and compares it to the pediatric model calibration:

TABLE 1

	RISK WEIGHT	
	PEDIATRIC MODEL	CONTROL MODEL
OTHER BACTERIAL INFECTIONS	$4,045	$5,410
BACTERIAL INFECTION IN OTHER DISEASES	$2,207	$5,410
OTHER VIRAL INFECTIONS	$93	$5,410
OTHER INFECTIONS	$392	$5,410
LYME DISEASE	$355	$5,410
BACTEREMIA	$13,126	$5,410

In addition, illnesses that are more important in a pediatric population, such as developmental disability, were refined in our model. Table 2 below shows the risk weights for the HCC category "other developmental disability" used in the control model and compares it to the pediatric model calibration.

TABLE 2

	RISK WEIGHT	
	PEDIATRIC MODEL	CONTROL MODEL
EMOTIONAL DISORDERS OF CHILDHOOD/ADOLESCENCE	$931	$830
LEARNING/DEVELOPMENT DISORDERS	$1,061	$830
UNSPECIFIED CHROMOSOMAL ANOMALIES AND CONGENITAL MALFORMATION SYNDROMES	$4,119	$830
SEX CHROMOSOME ABNORMALITIES (E.G., KLINEFELTER'S/TURNER SYNDROMES)	$7,550	$830

Results

This pediatric risk adjustment model has an R-squared of 58% on pediatric populations, which is a significant improvement from the control model's R-squared of 45%.

This increase in statistical fit will affect the financial results of organizations bearing financial risk for pediatric populations. For example, using the pediatric-only model on children in the data used to develop our model results in a risk score that is approximately 1.5% higher than the control model developed for a standard population.

Other considerations

The pediatric risk model we developed is intended for a commercially insured pediatric population and was designed to risk adjust total cost of care. As with any risk model, further fine-tuning to better reflect the business needs and the characteristics of a population under consideration is required. For example, in risk-based contracts where a subset of services is carved out, such as neonatal intensive care, the model may also need to be recalibrated to better reflect the scope of the global payment arrangement.

Conclusion

These results show that a risk model calibrated for a standard population has significantly lower predictive power if it is applied to a pediatric-only population. In alternative payment models that use risk adjustment to distribute payments to providers, this could also result in inequitable reimbursement to providers specializing in pediatric populations. As a result, providers specializing in serving pediatric populations should carefully review the risk models used in any alternative payment arrangement before participation.

Guidelines issued by the American Academy of Actuaries require actuaries to include their professional qualifications in all actuarial communications. Rob Parke and Howard Kahn are members of the American Academy of Actuaries, and meet the qualification standards for performing the analyses in this report.

Howard Kahn is a consulting actuary with Milliman's New York office. Contact him at howard.kahn@milliman.com.

Rob Parke is a principal and consulting actuary with Milliman's New York office. Contact him at rob.parke@milliman.com.

Rong Yi, is a senior consultant with Milliman's New York office. Contact her at rong.yi@milliman.com.

FOR MORE ON MILLIMAN'S HEALTHCARE REFORM PERSPECTIVE

Visit our reform library at www.milliman.com/hcr
Visit our blog at www.healthcaretownhall.com
Or follow us on Twitter at www.twitter.com/millimanhealth