

Comparison of Risk Adjusters for Medicaid-Enrolled Children With and Without Chronic Health Conditions

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Objective.—Several capitation payment systems have been developed and implemented recently by public and private insurers as well as by individual managed care organizations. Many pediatricians have expressed concern that methods for establishing capitation rates may not adequately account for the higher expected expenditures for children with chronic health conditions. In this study, we evaluate a demographic- and 4 diagnosis-based models, paying particular attention to their performance for children with chronic health conditions.

Methods.—We selected children 18 years of age and under who were enrolled in the Maryland Medicaid Program in 1995 and 1996. We defined the population of children with chronic health conditions using ICD-9 codes. Individual and group-level analyses were utilized to measure the ability of the different risk adjustment models to predict expenditures in 1996 based upon information available in 1995.

Results.—All 4 diagnosis-based models significantly outperformed the demographic model for children overall and for children with chronic health conditions. Differences between diagnosis-based models were small, especially as the size of test populations increased.

Conclusions.—Risk adjustment methods that account directly for health status promise to reduce incentives to exclude children with chronic illnesses from managed care plans and to provide a foundation for more appropriate payments to pediatricians who care for these children.

KEY WORDS: capitation payment systems; children; chronic illness; Medicaid; risk adjustment

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Analysis of nationally representative samples indicates that between 15% and 18% of the nation's children have a chronic condition.^{1,2} Increasing numbers of these children have enrolled in managed care systems during the last decade in both the public and private sectors.^{3–5} As state Medicaid programs become more experienced with managed care for healthy populations, children with chronic health conditions and disabilities, who often have been carved out of initial efforts to implement managed care programs,³ will be more likely to be incorporated into managed care plans. This will dramatically increase the number of children with chronic health conditions enrolled in managed care, especially children with severe chronic illness.

Many pediatricians, parent advocacy groups, and policy makers have expressed concern that enrollment in managed care organizations (MCOs) will pose a serious threat to access and quality of care for this group of vulnerable children.^{6–9} MCOs are concerned that they will not receive appropriate capitation rates and, therefore, will be unable to pay for the additional services provided to this vulnerable population.

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Capitation is a payment arrangement in which MCOs receive a fixed amount for each enrolled person, independent of the services actually provided to that specific person. In some managed care arrangements, MCOs then use the funds to pay capitated rates to pediatricians. In 1998, 97% of pediatricians were reported to have at least one managed care contract, and 61% of their revenue came from managed care plans.¹⁰ One concern is that capitation rates paid to MCOs or pediatricians may not reflect higher expenditures associated with children who have chronic illnesses and disabilities.^{11,12} Capitation rates that reflect expected expenditures for vulnerable populations, such as chronically ill children, are necessary if MCOs and capitated pediatricians are to provide appropriate care. Without adequate capitation payments, MCOs and capitated pediatricians face the incentive to cut costs by reducing care to these children, developing ways to discourage their enrollment, or encouraging their disenrollment.¹³

Several risk adjustment methods have been developed to set capitation payment rates that reflect expected expenditures for an individual or group of individuals.¹⁴ The first step in setting capitation rates is often referred to as risk assessment. This assessment uses data to classify individuals into separate categories, based on the expected use of medical services. The second step, risk adjustment, then estimates expenditures for each category.^{15,16}

Most risk adjustment models were originally developed for the Medicare program and have been applied to children without careful analysis or evaluation of their appropriateness. Over the last few years, some of the models have been implemented by a few Medicaid programs, are being phased in by the Medicare program,¹⁷ and are al-

ready being used by some MCOs and private insurers.^{15,18} However, little attention has been paid to comparing predictive accuracy of current versions of these models for children, especially children with chronic health conditions. The purpose of this analysis is to compare the predictive accuracy of commonly used models in a sample of children with and without chronic health conditions.

CAPITATION MODELS

This section briefly reviews the conceptual framework behind the various risk adjustment models that we are comparing. Initially, all models were based upon demographic characteristics. These characteristics (age, gender, etc) were shown to be poor predictors of current or future utilization or expenditures.^{14,18} As a result, the health service research community began developing models based on more predictive factors, such as functional status, self-reported health status, prior utilization, and diagnostic-based risk adjusters.^{7,14} After numerous evaluations, the consensus among most clinicians, health service researchers, policy makers, and MCOs was that clinically based risk adjusters were the most promising.^{7,14,16,18}

All of the models have several characteristics in common. All of them, for example, map the universe of diagnostic codes into a discrete number of groups that are then used to predict future expenditures. The models may or may not use additional information, such as demographic data, to group individuals. The mean expenditures for the group are then used to set the payment rate. The models differ primarily with respect to how they map the diagnostic codes and the final number of groups.

Ambulatory Diagnostic Groups

The primary and secondary diagnoses of the individual are combined into 32 Ambulatory Diagnostic Groups (ADGs). Diagnoses are placed into ADGs according to the following criteria: clinical similarity; a condition's expected persistence/recurrence over time; the patient's likelihood that he or she will have a return visit to continue treatment for a condition; the probability that a specialty referral will be required; the expected need and cost of diagnostic and therapeutic procedures associated with a condition; the patient's likelihood of requiring hospitalization for a condition during the near term; a condition's likelihood to result in short-term or long-term disability; and a condition's probability to lead to decreased life expectancy within the short or long term.¹⁹ The ADGs are not mutually exclusive, and individuals can be placed into several ADGs.

Adjusted Clinical Groups

The Adjusted Clinical Group (ACG) were developed by the same team that developed the ADG. The ACG uses the ADG categories as building blocks and combines them with patients' age and gender to create 83 mutually exclusive categories. The latest version of ACG classifies individuals by the diagnoses they receive in both ambulatory settings and inpatient services.¹⁹

Hierarchical Condition Category

The Hierarchical Condition Category (HCC) model groups all diagnostic information obtained from inpatient, outpatient, and physician services and patient age and gender into 545 clusters of closely related medical conditions. These clusters are aggregated into 118 condition categories based on their clinical similarity and cost implications. The HCC model then impose severity hierarchies on conditions within each category. Within a specific disease hierarchy, a person is characterized only by the most serious condition, whereas he or she still may be classified as having multiple conditions that fit across the hierarchies.^{20,21} The HCC system adds the predicted costs for each condition to calculate the total predicted costs.

Disability Payment System

The Disability Payment System (DPS) model was designed for child and adult Medicaid recipients with disabilities. It uses diagnostic information to form 701 "stage 1" clinical groups based on body system or particular type of illness. It then aggregates these groups into 43 "final groups" according to their association with higher future costs. Eighteen "hierarchical major categories" are constructed, so that if a person has a disease that is in a high-cost group, that individual cannot also be counted as being in a lower cost group with the same major classification.²²

Similarities and Differences Across Models

Except for the demographic model, all of the risk adjustment methods use clinical information (ie, ICD-9 codes) to create a set of patient groups according to severity of illness and potential costs of care. The methods differ in how they combine the specific ICD-9 codes to determine the groups. Thus, the same ICD-9 codes would be classified somewhat differently by each method. For example, children who have infantile cerebral palsy (unspecified, 343.9) are grouped into ADG10, which is called "Chronic Medical: Stable."¹⁹ The HCC method categorizes these patients into a group called "very high cost pediatric and congenital disorder."²⁰ The DPS groups these children into the "Central Nervous System: Low Cost" group.²²

During the last 5 to 7 years, states have begun to adapt and apply these models to their Medicaid programs. For example, Washington State uses a risk adjustment method based on HCC.²³ Maryland uses a modified ACG model to set their Medicaid capitation rates.²⁴ Colorado has begun to classify their disabled Medicaid recipients based on DPS.^{18,23} Private insurers and managed care plans are using all 3 models. Most applications have involved efforts to reduce the number of categories or groups in order to enhance administrative feasibility, and different states are likely to make somewhat different choices. Thus, even the same basic model may be applied in slightly different versions in two different states. For our purposes, we elected to assess each model's basic or core version and not how it might be applied in a particular state.

METHODS

Data Source and Population Sampling

This study utilized Maryland Medicaid claims data for 1995 and 1996. These data include beneficiaries' enrollment information and all service claims covered by Medicaid (eg, hospital inpatient, hospital outpatient, physician, pharmacy, home health, and dental care). We selected only children who were 18 years of age or younger. During these years, nearly all Medicaid payments in Maryland were based on a fee-for-service system. The sample frame for this analysis consisted of children who were enrolled in the Medicaid program for at least 6 months in 1995 and for at least 6 months in 1996. Infants were included in the study sample if they had at least 2 months of eligibility in 1995 and at least 6 months of eligibility in 1996. This is the shortest time frame in which accurate measures of health care utilization in 1995 and expenditures in 1996 could be obtained. Children in residential institutions were not included in the analysis.

Children With Chronic Health Conditions

For our purposes, this population includes a wide range of children with chronic illnesses and disabilities. Many studies have indicated that a small percentage of the population accounts for a very high percentage of total expenditure.⁷ Children with chronic health conditions are likely to be among these high-cost populations.¹¹ We used a method for identifying these children that was developed in previous studies.^{25,26} This method used a general classification of childhood chronic conditions based on ICD-9 codes. For example, children with asthma, diabetes, epilepsy, sickle cell disease, infantile cerebral palsy and related paralysis, cystic fibrosis and related disorders, malignancies, hemophilia, rheumatoid arthritis, spina bifida, and congenital anomalies are included. Most mental health conditions are not included in this categorization method. We identified the group of children with these conditions by mapping their inpatient, outpatient, and physician service records in Medicaid claim data. Using a single claim for asthma may lead to overestimation of children with this condition. Therefore, we used an algorithm to confirm the diagnosis of asthma by requiring at least 2 outpatient claims, or 1 hospitalization claim, or 1 emergency room visit.

Analytic Approach

Our overall objective was to estimate the predictive accuracy of each of the models; predictive accuracy was defined as the extent to which the model predicted actual costs in the following year based upon information available in the current year. Data from the first year were used to create groups according to the specifications of each model. Expected expenditures for each person were calculated based upon the model. Data from the second year were used to calculate the actual expenditures incurred by the person. A comparison of actual and predicted expenditures in the second year was used to judge the predictive accuracy of the various models.

We used 2 specific approaches to estimate the predictive accuracy of capitation methods. The first was individual-level analysis. In this approach, ordinary least-squares regression was used to assess how well each model predicts future expenditures. The dependent variable is the total amount of dollars paid by the Maryland Medicaid program in the second year. The regression generates an R^2 that ranges from 0 to 1. This R^2 represents the proportion of the future expenditure that can be predicted by the model. For example, an R^2 of 0.15 indicates that the model is able to use the current year's information to predict 15% of the variation in expenditures for the subsequent year.

The second approach involved group-level analyses. This approach divides the population into subgroups and estimates how well the models predict expenditure for each subgroup. These subgroups can either be "random" or "skewed." We used randomly selected groups to mimic how the risk adjustment models would perform for a group of people with no particular distinguishing characteristics. We used nonrandom or "skewed" groups to create populations that contain a disproportionate number of chronically ill children.

In the group-level analyses, split-half validation was employed to estimate the predictive performance, as measured by the predictive ratio, of each model. The predictive ratio is the predicted expenditure divided by the actual expenditure. We used the split-half validation method and randomly subset the data into 2 halves. The first half of data was used to estimate a model's parameters (coefficients of independent variables). These estimates were then applied to the second half of the data to calculate the predicted expenditure. If the predicted expenditure is very close to actual spending, the predictive ratio will be very close to 1. A value of 1.03, for example, indicates that the model overpredicts the average expenditure for a given group of people and, consequently, overpays health plans by 3%. An 0.95 predictive ratio indicates that the model will underpay the health plans by 5%. Appendix 1 provides further information regarding the split-half validation method and estimation of predictive ratios.

We used different techniques to separate our study populations into various random and nonrandom groups. First, we randomly sampled 50 groups of 500, 5000, and 25 000 children. This approximates the situation in which health plans of different sizes receive a random group of enrollees. We then summarized the results across all 50 groups to obtain the predictive ratio.

Frequently, when individuals have a choice among competing MCOs or among pediatricians or pediatric groups, the patient mix for a particular health plan is not random. MCOs and enrollees may select each other, depending on the way the insurance and health care delivery system is organized.¹⁸ Some health plans and providers (such as teaching hospitals or hospital-based pediatric practices) may have a higher percentage of patients who are "high risk" and who are more expensive. Information on individuals' previous expenditures, hospital admissions, or chronic conditions can be easily used by health plans to profile potential enrollees and to identify pre-

TABLE 1. Demographic Characteristics of the Study Sample

	N	%	Average Expenditure*
Total	109 515	100	1757
Age (years)			
<1	16 644	15.2	4091
1–5	38 108	34.8	936
6–14	44 588	40.7	1400
15–18	10 175	9.3	2587
Gender			
Male	54 904	50.0	1897
Female	54 640	50.0	1617
Race			
White	31 605	28.9	2372
African-American	72 005	65.7	1446
Others	5934	5.4	2262
Eligibility			
AFDC**	79 122	72.2	936
Non-AFDC	30 422	27.8	3893
Chronic condition			
Yes	12 357	11.3	9507
No	97 187	88.7	764

*Expenditure estimates are annualized.

**Aid to Families with Dependent Children

ferred populations. To explore how selection bias would affect payments under each capitation model, we sampled a series of nonrandom groups based on this information and compared the models' predictive performance for these groups.

The first nonrandom group was based on level of expenditure in the first year. Since about 40% of this population never or rarely utilized health services in a year,⁷ we divided the population into 6 groups based on their expenditures in the first year (0–50th, 51–60th, 61–70th, 71–80th, 81–90th, and 91–100th percentiles). The second group was based on hospital admissions in the previous year (no admission, 1 admission, and 2+ admissions). The third strategy created 5 subgroups of 5000 children each; in each subgroup, the percentage of individuals with a chronic health condition varied from 0% to 100% in increments of 20%.

Overall, the independent variables are, in the demographic model, individuals' demographic characteristics (age and gender) and Medicaid eligibility category of Supplemental Security Income program (SSI) or Aid to Families with Dependent Children (AFDC). For the diagnosis-based models, the independent variables include age, sex, Medicaid eligibility category, and the clinical groups created by each risk adjustment model based on the first year's diagnoses. Since the Medicaid recipients may have different duration of eligibility in the study period, the total expenditure per person was standardized to a yearly basis. Weights were used in the regression to reflect different duration of eligibility for each individual.

Sensitivity Analysis

The distribution of health expenditure across individuals is highly skewed. This skewness can produce biased and imprecise parameter estimates, thus compromising a model's ability to provide accurate predictions.⁶ We con-

TABLE 2. Predictive Accuracy for 3 Groups With Increasing Sizes*

N	Demographic	ACG	ADG	HCC	DPS
500	1.17	1.12	1.08	1.10	1.05
5000	1.04	1.04	1.03	1.02	0.97
25 000	1.03	0.99	1.01	1.00	1.01

*Abbreviations: ACG = Adjusted Clinical Group; ADG = Ambulatory Diagnostic Group; DPS = Disability Payment System; HCC = Hierarchical Condition Category.

ducted a sensitivity analysis with the truncation of total expenditures at \$50 000 and \$100 000. If an enrollee had a total expenditure amount exceeding \$50 000 (or \$100 000) for a year, this amount was set to \$50 000 (or \$100 000). We chose these 2 levels because they reflect many health plans' and states' policies regarding stop-loss reinsurance.²⁷ Truncating at \$50 000 and at \$100 000 simulates such a reinsurance approach and is a common strategy in risk adjustment analyses. The results of these analyses are presented in Appendix 2.

RESULTS

Using our criteria for length of Medicaid eligibility described above, 109 515 (33%) of the 336 928 noninstitutionalized children aged 0 to 18 years enrolled in the Maryland State Medicaid program in 1995 were selected as our study sample. This percentage reflects the traditionally high rate of short enrollment periods in the Medicaid population. Of these children, 15% were less than 1 year old, 72% were enrolled in AFDC, 66% were African-American, and 50% were male. Overall, about 38% of our study sample never used any health services during 1995. This relatively high percentage of nonusers may reflect utilization patterns among those who are consistently enrolled for 2-year period; the Medicaid population in general (including children who have short enrollment periods) is likely to have lower nonuse rates.²⁸ The average total expenditure per person per year was \$1757. About 11% of the sample had at least one chronic health condition, and expenditures for these children were about 13 times higher than those for children without a chronic health condition (see Table 1).

Individual-Level Analysis

In the demographic model, age, gender, and welfare factors were able to explain less than 1% of the variance in future expenditure. HCC and DPS models performed better than other models, with adjusted R^2 of 16% and 13%, respectively. ADG and ACG were able to explain 10% and 9%, respectively. These results indicate that any of the selected diagnosis-based risk adjustment methods perform substantially better than a demographic model that includes only age, gender, and Medicaid eligibility status.

Random Groups

For the split-half validation, all models performed almost equally well with large random samples, as Table 2 illustrates. The results based on 50 random groups of 500

TABLE 3. Predictive Accuracy for Selected Groups*

	Demographic	ACG	ADG	HCC	DPS
Expenditures (percentile)					
0–50th	3.50	1.50	1.46	1.50	1.70
51–60th	2.41	1.55	1.10	1.24	1.51
61–70th	1.79	1.56	1.14	1.11	1.30
71–80th	1.51	1.50	1.40	1.18	1.33
81–90th	0.79	1.20	1.12	1.03	1.09
91–100th	0.31	0.75	0.81	0.82	0.75
Hospital admission					
No admission	1.35	1.17	1.10	1.18	1.08
1 Admission	0.60	0.97	1.08	1.02	1.04
2+ Admissions	0.21	0.60	0.68	0.79	0.61
With chronic health conditions (%)					
0	1.71	1.31	1.25	1.15	1.18
20	0.71	0.92	0.95	1.05	0.93
40	0.52	0.89	0.96	0.98	0.97
60	0.48	0.94	0.99	1.00	0.93
80	0.40	0.90	0.95	0.94	0.93
100	0.35	0.84	0.90	0.95	0.87

*Abbreviations: ACG = Adjusted Clinical Group; ADG = Ambulatory Diagnostic Group; DPS = Disability Payment System; HCC = Hierarchical Condition Category.

children show that the demographic method would overpay health plans by 17%, compared to ACG (+12%), ADG (+8%), HCC (+10%), and DPS (+5%). The predictive accuracy increases substantially for all models when the sample size increases to 5000, and it increases slightly when sample size increases to 25000. The predictive ratios based on 50 random groups of 25000 children show that the demographic model would overpay managed care plans by 3%. ADG and DPS would overpay by 1%. ACG would underpay by 1%, and HCC would pay the plans the exact amount of the actual costs.

These results indicate that, when using large random groups, the prediction errors for individuals tend to cancel each other out. In this case, even the demographic model based on age, sex, and Medicaid eligibility can predict expenditures that are very close to actual spending. The need to have diagnosis-based risk adjustment models becomes less important. However, as described earlier, the patient mix may not be distributed randomly among health plans or capitated providers; as a result, nonrandom groups are needed to compare each model.

Nonrandom Groups

Previous Expenditures

When nonrandom groups were created based on prior use of health care resources or previous diagnoses, all diagnosis-based models outperformed the demographic model. As Table 3 shows, all models will overpredict expenditures for individuals with relatively low expenditures and underpredict expenditures for those with higher expenditures in the previous year. This bias increases with the size of previous expenditures. Most children in the 0–50th percentile group were the children who consumed no or very little medical resources in the previous year. For this group, the demographic model will overpay health plans by 350%, compared to ACG (+50%), ADG (+46%), HCC (+50%), and DPS (+70%). For the group

in the 81–90th percentile, the demographic model underpredicts future expenditures by 21%. ACG and ADG overpredict by 20% and 12%, respectively. HCC generates the most precise prediction, overpredicting by 3%. For the group of children who cost the most (90–100th percentile), all models substantially underestimate expenditures in the subsequent year. These underestimates vary from 69% for the demographic model to 25% for ACG and DPS and to 19% for ADG and HCC.

Previous Hospital Admission

For the group of children who never used any inpatient service in the first year, the demographic model will overpay the health plans by 35%, compared to ACG (+17%), ADG (+10%), HCC (+18%), and DPS (+8%) models. For the group of children who were hospitalized at least twice, the demographic model substantially underpredicts actual spending (–79%), compared to ACG (–40%), ADG (–32%), HCC (–21%), and DPS (–39%) models.

Chronic Health Conditions

For the group of children who do not have chronic illness, the demographic model overpredicts payments by 71%, compared to ACG (+31%), ADG (+25%), HCC (+15%), and DPS (+18%) models. When the percentage of children who had a chronic health condition increases to 20%, all models will underpay, except for the HCC model, which will overpay by 5%. When the percentage of children with chronic conditions increases to 60%, the demographic model underpredicts the expected expenditure by 52%, compared to ACG (–6%), ADG (–1%), and DPS (–7%). HCC predicts the actual cost. When the percentage of children with chronic health conditions increases to 80%, all models underpay the health plans: demographic (–60%), ACG (–10%), ADG (–5%), HCC (–6%), and DPS (–7%).

DISCUSSION

This study compared a demographic model and 4 diagnosis-based models using data from the Maryland Medicaid program. It measured and compared the predictive performance of these models. Two approaches were utilized for the analysis: individual-level (entire samples) and group-level (random and nonrandom) approaches.

Our analyses indicate that at the individual level, all diagnosis-based models outperform the demographic model based on age, sex, and Medicaid eligibility by a wide margin. The demographic model explains less than 1% of the total variance in individual expenditures, whereas 9% to 16% of future expenditure can be predicted by the diagnosis-based models.

We used 3 random groups (500, 5000, and 25 000) to represent 3 different sizes of random pediatric populations. For plans with small enrollment (eg, 500 children), all models overpay plans, with a demographic model overpaying by the highest margin. As enrollment increases, margins of overpayment decrease. For plans with enrollment of 25 000 children, all models perform similarly, with predictive errors ranging from 1% to 3%.

We used a series of nonrandom groups to model what could happen if the groups were not random and if children with certain characteristics were disproportionately represented in certain groups. These groups were created based on their prior use (hospital admission and total expenditure) and medical conditions (chronic health conditions). When health plans provide coverage to healthy children—those who used few or no outpatient services, those who were not admitted to the hospital, and those who had no chronic conditions or disability in the previous year—all methods will overpay the health plans. For health plans that enroll more children with high expenditures, children with more than 2 hospital admissions, and children with chronic health conditions, all models will underpredict their costs in the subsequent year. This finding indicates that the use of any of the health status risk adjustment models may help to decrease the likelihood that health plans and capitated providers will seek to enroll only healthy patients. Each model is able to do a better job of prediction than the other 3 models for some groups. As a result, it is impossible to decide which of the 4 models is the best when using the criterion of predictive accuracy. Madden and colleagues²⁹ came to a similar conclusion using a different population and a somewhat different set of models. No method of risk adjustment, however, will solve completely the problem of selection bias.

This study evaluates selected risk adjustment models by simulating different enrollment patterns that can occur in actual practice. Our analyses provide insight into the predictive accuracy across selected models. The analyses did not account for other important factors, such as administrative feasibility, protection of sensitive patient data, and ability to resist gaming. We did not account for the frequency of short enrollment periods that is characteristic of many children in the Medicaid population. Further-

more, simulations will never capture entirely the complexities of the health care system. Our results can inform decision making regarding risk adjustment strategies, but many factors must be considered in the actual selection and implementation of any particular method. In actual application, each model will be modified slightly to accommodate particular situations.

Other models are under development that may provide yet more alternatives to selecting an appropriate method for a given situation.^{30–32} One example of these models is termed the Clinical Risk Groups. In this model, groupings were developed based on decisions by general and subspecialty pediatricians using ICD-9-CM and CPT-4 procedure codes.³⁰ This method classifies patient populations by presence, type, and severity of chronic health conditions and presence of significant acute conditions. Released in 2000 by 3M, this model will require independent field testing to assess its utility in comparison to current methods. In addition, it is anticipated that the existing models will undergo revisions.

To assure adequate access to quality care, children with chronic illness or disability need a payment system that compensates health plans or capitated providers for the additional costs associated with serving this population. The demographic model, the most common method, does not differentiate the financial risk of serving children with greater-than-average expected costs. The new generation of capitation models, which take into account the health status of enrollees, promises to reduce incentives for health plans to select low-cost populations and to under-serve high-cost populations once they are enrolled.

Methods of financing of health care are likely to evolve rapidly in response to changes in political priorities, industry experience, and consumer demands. It is imperative for pediatricians and other child health professionals to understand key concepts in rate setting so that they can participate actively in emerging debates to assure that vulnerable populations of children are protected.

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Appendix 1

The split-half validation method involved randomly partitioning the data into 2 halves. The first half of the data was used to develop the model and to determine coefficients (or weights). Based on their diagnoses (ICD-9 codes) in the first year, individuals were classified into particular “risk groups” according to each model's specifications. These risk groups, along with other demographic variables (eg, age and gender), were applied as predictors in a multiple liner regression constructed as follows:

$$\begin{aligned} \text{Total expenditure in year 1} \\ = \beta_0 + \beta_1 (\text{age}) + \beta_2 (\text{sex}) + \beta_3 (\text{risk groups}) \end{aligned}$$

The β coefficients (or weights) obtained from this regression were then applied to the second half of the data set using a similar regression model to determine the expected expenditure for the second year:

$$\begin{aligned} \text{Predicted expenditure for year 2} \\ = \beta_0 + \beta_1 (\text{age}) + \beta_2 (\text{sex}) + \beta_3 (\text{risk groups}) \end{aligned}$$

Model performance was evaluated by comparing predicted expenditure with actual expenditure of the second year. The closer this predictive ratio comes to 1.0, the better the performance of the model for that population. Specifically,

$$\begin{aligned} \text{Predictive ratio} \\ = \text{predicted expenditure/actual expenditure} \end{aligned}$$

Appendix 2

Individual-Level Analysis (R^2)

When the expenditures were truncated to reflect the common practice of stop-loss reinsurance, all models were able to explain more variation of the expenditures in the second year. At \$50 000 truncation, HCC reported an R^2 of 21.6%, followed by DPS (19.5%), ADG (16.6%), ACG (13.9%), and the value associated with the Demographic model (0.6%). When the payments were truncated at \$100 000, the value of R^2 for HCC was 18.8%, compared to DPS (16.8%), ADG (13.3%), ACG (13.9%), and the value associated with the Demographic model (0.5%). Overall, HCC and DPS models consistently show better performance with and without taking into account of stop-loss reinsurance.

Random Groups (Predictive Accuracy)

See Table 4.

Nonrandom Groups (Predictive Accuracy)

See Table 5.

TABLE 4. Predictive Accuracy for 3 Groups With Expenditures Truncated at \$50 000 and \$100 000*

N	Demographic		ACG		ADG		HCC		DPS	
	\$50K	\$100K	\$50K	\$100K	\$50K	\$100K	\$50K	\$100K	\$50K	\$100K
500	1.13	1.16	1.06	1.08	1.05	1.06	1.05	1.07	1.01	1.04
5000	1.02	1.05	1.01	1.00	0.99	1.01	0.97	1.01	0.94	0.96
25 000	1.01	1.01	1.00	1.01	0.99	1.00	1.00	1.00	0.99	0.99

*Abbreviations: ACG = Adjusted Clinical Group; ADG = Ambulatory Diagnostic Group; DPS = Disability Payment System; HCC = Hierarchical Condition Category.

TABLE 5. Predictive Accuracy for Selected Groups With Expenditures Truncated at \$50 000 and \$100 000*

	Demographic		ACG		ADG		HCC		DPS		
	\$50K	\$100K	\$50K	\$100K	\$50K	\$100K	\$50K	\$100K	\$50K	\$100K	
Expenditures (percentile)											
0–50th		3.40	3.46	1.48	1.48	1.40	1.44	1.38	1.44	1.58	1.62
51–60th		2.01	2.15	1.45	1.49	1.08	1.10	1.20	1.18	1.36	1.43
61–70th		1.51	1.64	1.45	1.50	1.09	1.12	1.05	1.08	1.15	1.22
71–80th		1.17	1.21	1.40	1.45	1.30	1.36	1.10	1.24	1.20	1.27
81–90th		0.72	0.77	1.10	1.14	1.06	1.09	1.00	1.01	1.02	1.06
91–100th		0.30	0.29	0.70	0.70	0.78	0.78	0.79	0.80	0.69	0.71
Hospital admission											
No admission		1.27	1.24	1.10	1.12	1.05	1.08	1.14	1.15	1.01	1.05
1 Admission		0.59	0.60	0.94	0.96	1.05	1.05	0.99	1.01	0.94	0.97
2+ Admissions		0.20	0.20	0.55	0.58	0.60	0.64	0.77	0.77	0.55	0.55
Chronic conditions (%)											
0		1.71	1.76	1.25	1.27	1.20	1.22	1.09	1.13	1.12	1.15
20		0.68	0.70	0.89	0.91	0.92	0.95	1.01	1.04	0.88	0.91
40		0.50	0.50	0.84	0.86	0.88	0.91	0.96	0.99	0.92	0.95
60		0.44	0.44	0.90	0.98	0.95	0.99	0.95	0.98	0.86	0.91
80		0.36	0.38	0.85	0.88	0.88	0.81	0.89	0.91	0.87	0.87
100		0.32	0.32	0.80	0.81	0.89	0.93	0.93	0.93	0.78	0.82

*Abbreviations: ACG = Adjusted Clinical Group; ADG = Ambulatory Diagnostic Group; DPS = Disability Payment System; HCC = Hierarchical Condition Category.