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RESEARCH ARTICLE

Risk-Adjusted Capitation Rates for Children: How Useful Are the Survey-Based Measures?

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Objective. Despite the recognition by some experts that survey measures have the potential to improve capitation rates for those with chronic conditions, few studies have examined risk-adjustment models for children, and fewer still have focused on survey measures. This study evaluates the performance of risk-adjustment models for children and examines the potential of survey-based measures for improving capitation rates for children.

Data Sources. The study sample includes 8,352 Medicaid children who were followed up for 2 years by the Medical Expenditure Panel Survey in 2000–2005.

Study Methods. Children's information in 1 year was used to predict their expenditures in the next year. Five models were estimated, including one each that used demographic characteristics, subjectively rated health status, survey measures about children with special health care needs (CSHCN), prior year expenditures, and Hierarchical Condition Category (HCC), which is a diagnosis-based model. The models were tested at the individual level using multiple regression methods and at the group level using split-half validation to evaluate their impact on expenditure predictions for CSHCN.

Principal Findings. The CSHCN information explained higher proportion of the variance in annual expenditures than the subjectively rated health status, but less than HCC measures and prior expenditures. Adding the CSHCN information into demographic factors as adjusters would remarkably increase capitation rates for CSHCN.

Conclusions. Survey measures, such as the CSHCN information, can improve risk-adjustment models, and their inclusion into capitation adjustment may help provide appropriate payments to managed-care plans serving this vulnerable group of children.

Key Words. Risk adjustment for resource use or payment, child and adolescent health, chronic disease, Medicaid, payment systems, capitation/risk-adjusted payments

Public insurance programs for children, including Medicaid and SCHIP, have increasingly relied on contracting with managed care as a mechanism of cost containment. For example, Medicaid managed-care enrollment as a fraction

of total Medicaid enrollment increased from 56 percent in 1999 to 71 percent in 2008 (CMS 2008). As capitation rates paid to managed-care plans in most states are not adequately risk adjusted for high-cost children, the plans have incentives to engage in risk selection—encouraging enrollment of low-risk, low-cost children (i.e., cream skimming) while discouraging enrollment of high-risk, high-cost children (i.e., dumping). To protect children who are expected to have high costs, some experts have proposed a number of mechanisms to reduce health plans' incentives for risk selection (Fletcher 1999; Feder et al. 2001), including the use of risk-adjusted capitation rates to reflect the expected cost of child enrollees. Most published studies of risk adjustment, however, have centered on adults, especially the elderly enrolled in Medicare managed-care plans. Few risk-adjustment models have been estimated specifically for children (Newhouse et al. 1993; Fowler and Anderson 1996; van de Ven and Ellis 2000; Hwang, Ireys, and Anderson 2001).

This study aims to fill the information gap by evaluating the performance of risk-adjustment models for children. In particular, we extend the current literature in two ways. First, we estimate risk-adjustment models for children using survey measures, which have the potential to improve capitation rates for the elderly with chronic conditions (Zaslavsky and Buntin 2003) but have not been included in pediatric risk-adjustment models yet.

Second, we compare the predictive power of different risk adjusters for all children, and specifically for children with special health care needs (CSHCN; see McPherson et al. 1998), who can be identified through parents report in household survey. To our knowledge, our paper is the first study of risk adjustment for CSHCN. In particular, we examine whether adding CSHCN information into risk-adjustment models improves the models' predictive power.

We pay particular attention to CSHCN for three reasons. (i) The past two decades have witnessed an increase in the number of CSHCN. Recent studies have shown that 10.2 million American children had special health care needs in 2005, compared with 9.4 million in 2001 (Blumberg 2003). (ii) CSHCN have been considered especially vulnerable in the current marketplace dominated by managed-care plans because they have poorer health status, used more health services, and incurred higher expenditures than other children (Newacheck and Taylor 1992; Fox and Newacheck 1993; Neff and

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Anderson 1995; Edmunds and Coye 1998; Liptak et al. 1998; Newacheck et al. 2000; Stein 2001; Szilagyi et al. 2003; Newacheck and Kim 2005; Liptak et al. 2006). (iii) CSHCN have drawn intense attention from policy makers. For example, meeting the needs of CSHCN was established as an important public health objective for the nation as indicated by the Healthy People 2010 (Department of Health and Human Services 2000). In addition, a key priority identified by the federal Maternal and Child Health Bureau stated that "Families of CSHCN will have adequate private and/or public insurance to pay for the services that they need" (McPherson et al. 2004).

In this paper, we first evaluate the performance of different risk adjusters for children and then analyze how they could affect payments for health plans (capitation rates) serving CSHCN. Finally, we will discuss implications of our study findings and identify directions for future work.

METHODS

Data

The Medical Expenditure Panel Survey (MEPS) is a series of nationally representative surveys designed by the Agency for Healthcare Research and Quality to continually provide timely, comprehensive information about health care use and costs in the United States (Cohen, Monheit, and Beauregard 1996). Since 2000, the MEPS started to identify CSHCN using an instrument called the CSHCN Screener. The Screener has five stem questions on general health care needs (Bethell et al. 2002), each of which has two follow-up questions to determine whether the health care need is the consequence of chronic health conditions. Those who affirmatively answer one of the stem questions and its two follow-up questions are considered to have a special health care need. These questions provide both health status information, such as functional limitation, and clinical information, such as prescribed medicine and special therapy, which could potentially be used for risk adjustment.

The study sample includes 8,352 Medicaid-enrolled children who were followed for 2 years by the MEPS in 2000–2005. Of these, 1,664 were CSHCN. Accounting for the MEPS sampling design, we estimate that CSHCN comprise 21 percent of Medicaid-enrolled children nationally.

Model

All children in our sample contribute 2 years of data. We develop a model that uses children's information from the first year to predict their expenditures in

the second year. For the normalized risk score generated for each child by the Hierarchical Condition Category (HCC) software (see more information below), we estimate an ordinary least-square (OLS) model. For other risk adjusters, we specify a modified two-part model, first developed for the RAND Health Insurance Experiment and then widely used in health services research (Duan et al. 1983; Manning 1998; Ai and Norton 2000; Manning and Mullahy 2001; Bao 2002) and for risk adjustment (Newhouse et al. 1993). The model's first part estimates the probability that a child used any health services, and the model's second part analyzes the total expenditure of children who used health services. The first equation is specified as a multivariate logistic regression. Let U be an indicator of any health service use. Then

$$\text{Logit}\,(U) = \alpha_1 + \beta_1 X_i \tag{1}$$

The second equation is specified as a continuous function of total expenditures (Y) as

$$Y = \alpha_2 + \beta_2 X_i \tag{2}$$

where equation (2) is estimated with generalized linear model (GLM) using a Poisson distribution and log link. Although researchers have used a variety of statistical models for expenditure data, there is no current consensus about the best model (Mullahy 1998; Blough, Madden, and Hornbrook 1999; Etzioni and et al. 1999). Manning and Mullahy (2001) made an important contribution in this area by comparing a number of alternative estimation approaches, including the GLM, and the OLS model with a logged dependent variable. Following their recommendations, we first checked the log-scale residuals from the OLS model to test for heteroscedasticity. As indicated by both the Breusch–Pagan test and the Park test, the residuals were heteroscedastic in continuous variables, making it very hard to form the appropriate smearing retransformation factors for the log OLS. Because the current literature offers no easy fix for this problem, we did not further consider the OLS model. Instead, we turned to the GLM, and we went through the following statistical procedures to ensure that it was appropriate for our application. We applied a modified Park test proposed by Manning and Mullahy (2001) to check the residuals of the GLM, and we failed to reject the Poisson distribution. The GLM with Poisson distribution and log link passed the Pregibon Link test and a variant of Hosmer and Lemeshow test for goodness of fit for linearity. The model was also not overfit, as indicated by the Copas analysis, which is cross-validation using split-sample method with bootstrapping. We also compared OLS and GLM in terms of bias—the difference between predicted and

observed expenditures—and found that the average bias for GLM was smaller than that for log OLS. Thus, we chose the GLM with Poisson distribution and log link for this study.

Dependent Variables

The dependent variable for the logistic regression model is a dichotomous indicator of the use of health services. The dependent variable of the GLM is a measure of total annual expenditures, which is defined in the MEPS as "the sum of direct payments for care provided during the year, including out-of-pocket payments and payments by private insurance, Medicaid, Medicare, and other sources" (Agency for Healthcare Research and Quality 2003). Indirect payments, such as Medicaid Disproportionate Share, are not included. The MEPS data also do not include expenditures on over-the-counter drugs and alternative care services.

Explanatory Variables or Potential Risk Adjusters

As Table 1 shows, we construct five sets of adjusters. First, like the adjusters used by Medicaid or SCHIP in many states, we use age and gender to estimate a basic model, to which the following sets of adjusters are added.

Subjectively Rated Health Status. Five categorical variables that indicate parents' perceptions of their children's health status, including (1) perceived health status (excellent, very good, good, fair, and poor), (2) perceived mental health status, (3) whether the child seems less healthy than other children, (4) whether the child has never been seriously ill, and (5) whether the child usually catches whatever is going around. Although researchers have raised concerns about using such variables as adjusters because of the possibility of fraud and cost of data collection (Newhouse 1986), we use them to compare with CSHCN information in terms of performance as adjusters.

CSHCN Information. Six variables including one dichotomous variable that indicates a child had a special need, and five dichotomous variables that indicate the five types of special needs. The types of special needs are identified by the five questions of the CSHCN Screener, including need or use of prescription drug, having limitation, need or use more health care than is usual for other children of the same age, need or use special therapy, needing or using counseling for at least 12 months.

Table 1: Definition of Adjusters

Adjuster	*Definition*
Demographic factors	
Age	Continuous variable; coded 0–17
Sex	Dichotomous variable; 1 = male, 2 = female
Subjectively rated health status	
Perceived health status	Parents' rating of child's health status, 1 = excellent, very good, or good; 0 = fair or poor
Perceived mental health status	Parents' rating of child's mental health status, 1 = excellent, very good, or good; 0 = fair or poor
Child never seriously ill	Parents' report on whether the child has never been seriously ill; 1 = yes, 0 = no
Child less healthy than other children	Parents' report on whether the child seems to be less healthy than other children; 1 = yes, 0 = no
Child usually catching diseases that are going around	Parents' report on whether the child usually catches disease that are going around; 1 = yes, 0 = no
CSHCN information	
CSHCN status	Whether the child was considered to have a special care need; 1 = yes, 0 = no
Need of prescription	One of the 5 special needs identified by the CSHCN Screener—child needing or using prescription drug for at least 12 months; 1 = yes, 0 = no
Need of more health care	One of the five special needs identified by the CSHCN Screener—child needing or using more health care than is usual for other children of the same age for at least 12 months; 1 = yes, 0 = no
Limitation	One of the five special needs identified by the CSHCN Screener—child having limitation to do things most children of the same age can do for at least 12 months; 1 = yes, 0 = no
Need of special therapy	One of the five special needs identified by the CSHCN Screener—child needing or using special therapy for at least 12 months; 1 = yes, 0 = no
Need of counseling	One of the five special needs identified by the CSHCN Screener—child needing or using counseling for at least 12 months; 1 = yes, 0 = no
Prior use and expenditures	
Total expenditures in the prior year	Continuous variable
Hierarchical Condition Category (HCC)	184 categories of medical conditions developed by DxCG Inc., using the ICD-9 codes

Note. The CSHCN Screener questions were asked to parents of children in the MEPS. If the parents answered affirmatively to any type of the five special needs (prescription, more health care, limitation, special therapy, counseling), then the child would be considered to have a special health care need.

CSHCN, children with special health care needs; MEPS, Medical Expenditure Panel Survey.

Prior Year Expenditures. A continuous variable representing a child's total annual expenditures in the prior year.

HCC. Developed by researchers at DxCG Inc., the HCC model is based on the ICD-9 diagnosis codes. Each ICD-9 code is classified into one of 184 condition categories, and hierarchies are further imposed to make predictions more robust to variations in how disease codes are captured, to reward specific coding, and to increase model stability. Among the currently available risk-adjustment models, we chose the HCC model because (1) previous studies have found that it performed relatively well on pediatric populations (Fowler and Anderson 1996; Hwang et al. 2001), and (2) it has been successfully implemented on the MEPS data, which include diagnosis information, such as ICD-9 codes (Agency for Healthcare Research and Quality 2008).

Because previous studies indicated that the model with prior year expenditures and the HCC model performed relatively better for children (Newhouse et al. 1993; Hwang et al. 2001), we add CSHCN information to each of the two models to examine what the information does on top of those models.

Indicator of Adjusters' Performance

Following the study by Newhouse et al. (1993), we calculate the following measure of R^2 as an indicator of the risk adjusters' performance, which is the usual measure of R^2 in the case of a linear model, but can be calculated only by statistical programming for nonlinear models such as ours.

$$R^2 = 1 - \sum \left(y_i - y\_\text{hat}_i\right)^2 / \sum \left(y_i - y\_\text{bar}\right)^2,$$

where y_i is the actual expenditure by the ith child, y_bar is the mean of actual expenditures by the study sample, $y\_\text{hat}_i = P_i \times C_i$, P is the predicted probability of using health services from the first part, and C is the annual expenditure predicted from the second part.

As in previous studies of risk adjustment (Fowler and Anderson 1996; Hwang et al. 2001), we performed cross-validation of the above risk-adjustment models using a split-sample method. The split-sample method results in the random partitioning of the data into two halves. The first half was used to estimate the model, and the second half was used for prediction. For the second half of the split sample, we calculated a predictive ratio, which is

equal to the average predicted expenditures divided by the average actual expenditures. We used the ratio to serve two purposes (Fowler and Anderson 1996; Hwang et al. 2001). First, it is an indicator of model performance.

While the predictive ratio for the entire sample is one, it is not necessarily the case for the second half of the split sample. The closer this ratio comes to one for the second half, the better the performance of the model. Second, the predictive ratio is an indicator of over or underpayment for subgroups. If it is less than one for a group, then it suggests that the group will be underpaid under the risk-adjustment model. If it is more than one for a group, then it suggests that the group will be overpaid under the risk-adjustment model. In this study, we calculated the predictive ratios for CSHCN and non-CSHCN in the second half of the split sample, respectively.

RESULTS

Table 2 shows the percentage of annual expenditures explained by different adjusters. Demographic factors explained about 0.2 percent of the variance in

Table 2: Percentage of Annual Expenditures Explained by Different Adjusters

Adjusters	*%*	*% Reported by Prior Studies*
Age+sex	0.2	0.07**
Age+sex+subjectively rated health status	3.9	5.1*
CSHCN information as adjusters		
Age+sex+CSHCN status	3.3	—
Age+sex+need of prescription	3.2	—
Age+sex+need of more health care	4.7	—
Age+sex+need of ability limitation	3.1	—
Age+sex+need of special therapy	3.4	—
Age+sex+need of counseling	1.9	—
Age+sex+all CSHCN information	7.3	—
Age+sex+HCC	12.1	5.32**, 16***
Age+sex+prior use	43.5	20.7*
Age+sex+all CSHCN information+HCC	13.5	—
Age+sex+all CSHCN information+prior use	48.5	—

* Newhouse et al. 1993.

** Fowler and Anderson 1996.

***Hwang, Ireys, and Anderson 2001.

CSHCN, children with special health care needs; HCC, Hierarchical Condition Category.

annual expenditures, a very small proportion. Subjectively rated health status measures offered some additional explanatory power, increasing the explained proportion to 3.9 percent when they were added to the demographic factors. The explanatory power also increased when each type of special needs was combined with the demographic factors. For example, need of prescription drug plus age and gender explained 3.2 percent of the variance in annual expenditures, a proportion similar to that explained by the dichotomous variable of CSHCN status (3.3 percent). In particular, together with demographic factors, all the information about CSHCN explained 7.4 percent of variance in annual expenditure, nearly double that explained by demographics plus subjectively rated health status information, but less than that explained by demographics plus HCC (12.1 percent). Adding the CSHCN information into the HCC model slightly increased the explained proportion to 13.5 percent. Demographics plus prior expenditures explained 43.5 percent. Putting the CSHCN information together with prior expenditures increased the explained proportion to 48.5 percent.

Table 3 presents the predictive ratios for the second half of the split sample under different models. With a predictive ratio of 1.00, the model with prior expenditure plus the CSHCN information has better performance than

Table 3: Predictive Ratios for the Second Half of the Split Sample

Adjusters	*Second Half*	*CSHCN in the Second Half*	*Non-CSHCN in the Second Half*
Age+sex	0.98	0.42	1.61
Age+sex+subjectively rated health status	0.97	0.57	1.42
CSHCN information as adjusters			
Age+sex+CSHCN status	0.98	0.99	0.96
Age+sex+need of prescription	1.00	0.86	1.17
Age+sex+need of more health care	0.97	0.81	1.14
Age+sex+need of ability limitation	0.95	0.59	1.36
Age+sex+need of special therapy	0.97	0.55	1.44
Age+sex+need of counseling	0.96	0.62	1.34
Age+sex+all CSHCN information	0.97	0.98	0.96
Age+sex+HCC	0.98	0.55	1.48
Age+sex+prior use	1.07	0.67	1.52
Age+sex+all CSHCN information+HCC	0.97	0.97	0.97
Age+sex+all CSHCN information+prior use	1.00	1.03	0.97

Note. The split-sample method results in the random partitioning of the data into two halves. The first half was used to estimate the model, and the second half was used for prediction. For the second half of the split sample, we calculated a predictive ratio, which is equal to the average predicted expenditures divided by the average actual expenditures.

CSHCN, children with special health care needs; HCC, Hierarchical Condition Category.

other models. Table 3 also shows the predictive ratios for CSHCN and non-CSHCN in the second half of the split sample. If only demographic factors were used as adjuster, the predictive ratio for CSHCN was 0.42, suggesting considerable underpayment for CSHCN and relative overpayment for non-CSHCN. The ratio increased to 0.98 when all the information about CSHCN was added to demographics. The two models with HCC and prior expenditures also resulted in underpayment for CSHCN. Adding the CSHCN information into each of the two models increased the predictive ratio for CSHCN to 0.97 and 1.03, respectively. These findings suggest capitation rates for CSHCN would be dramatically increased when the risk-adjustment model included the CSHCN information. This shows that the CSHCN information could help reduce the incentive for adverse selection by increasing capitation payments for them.

Conclusion and Discussion

This study found that the CSHCN information explained a higher proportion of the variance in annual expenditures than the subjectively rated health status, but less than HCC and the prior expenditures. These results are consistent with the findings reported in the literature (Newhouse et al. 1993; Fowler and Anderson 1996; Hwang et al. 2001), as shown in column 3 of Table 2. As in previous studies of risk adjustment, we found that prior use is the single powerful predictor of expenditures (van de Ven and Ellis 2000).

Our analysis also indicated that neither the HCC model nor the model with prior spending effectively predicts for the group of CSHCN despite previous reports that they performed relatively well for all children (Newhouse et al. 1993; Hwang et al. 2001). Using either of these two models would result in considerable underpayment for CSHCN. On the other hand, adding the CSHCN information to each of the two models would substantially increase capitation rates for CSHCN, reducing the adverse selection incentive against this group of children. Together these findings suggest CSHCN information could be useful risk adjusters for setting capitation rates.

As the first study using the survey-based CSHCN information as a risk adjuster, this paper takes advantage of comprehensive MEPS data on children's expenditures. In the literature, survey-based measures of health status and health needs have not been included in the studies of risk adjustment because most researchers have focused attention on models with detailed diagnostic and clinical data. As Zaslavsky and Buntin (2003) argued, survey measures have a number of advantages compared with alternative adjusters.

These measures are easy to collect; contain information, subjective or not, not always available in the medical record; are predictive of costs; and are less sensitive to care provision and data management than measures of utilization and diagnoses. For the purposes of our study, the information about CSHCN, which we use for risk adjustment, is easily obtained from parents based on the CSHCN Screener and could easily be verified by health care providers. In particular, "the policy research community has converged in its support for this mechanism [of identifying CSHCN through the CSHCN Screener]" (Davidoff 2004), which has been adopted by national surveys, including the MEPS. Previous studies have reported that the CSHCN Screener is cost-effective in comparison with other instruments to identify CSHCN (Bethell et al. 2002a, b; Blumberg et al. 2003). In particular, the mean household administration time for the CSHCN Screener was as short as 2 minutes and 6 seconds (Blumberg et al. 2003). This may avoid cost concerns of using the CSHCN Screener measures as adjusters. Another advantage is that the CSHCN information may not be overstated by parents for insurance purposes because they may be reluctant to claim their healthy kids have special needs. This implies that the use of CSHCN information as an adjuster may not be particularly susceptible to gaming, though additional research about this question is clearly warranted. Although we found that the use of survey-based measures could improve risk-adjusted capitation rates, concerns about their acceptability as risk adjusters could delay their use. Thus, continued work by the research community to expand the evidence about their potential and to build the case for their reliability may be essential for the adoption of survey-based measures in risk-adjusted capitation rates.

One criticism of survey measures as adjusters is that they do not obtain the level of predictive power that is possible with clinical data. This is true either for the model with the dichotomous variable of CSHCN status (explaining 3.3 percent of the variance in annual expenditures) or for the models with one of the five types of special needs (with the explained proportion between 2 and 5 percent). Our analyses show, however, that all the CSHCN information explained 7.3 percent of the variance in annual expenditures, compared with 12.1 percent by the diagnosis-based HCC model. The performance of the CSHCN information for risk adjustment is impressive if one considers the ease with which it can be obtained from household survey, particularly in comparison with the cost of obtaining detailed clinical information required by the HCC and other diagnosis-based models. Our results also indicate that neither the dichotomous variable of CSHCN status nor any one variable of the five special needs has strong explanatory

power. To improve the model performance, all the information about CSHCN should be included in the risk-adjustment model.

This study has several advantages over prior research on risk adjustment for children. In the first study of risk adjustment for children, for example, Newhouse et al. (1993) used data that included outpatient expenditure only, and that were limited to children ages 14 and older. Another study by Fowler and Anderson used data on paid claims and gross eligible charges for the study population of children. Their analyses might underestimate total expenditures (Fowler and Anderson 1996). In comparison, this study uses data from the MEPS, a nationally representative survey, covering all children of ages 0–18. In particular, the MEPS is unparalleled for the degree of detail in its data about health care expenditures as well as its ability to link data on health expenditures to the demographic, economic, health status, and other characteristics of survey respondents (Cohen et al. 1996).

Although we found that the CSHCN information can be useful for risk adjustment, our risk-adjustment models still explained only a small proportion of the variance in expenditures. There are also limitations in our study based on the MEPS data. First, the MEPS excludes institutionalized children, and, although fewer than 100,000 in 1990 (Newacheck et al. 2000), their exclusion could affect the analyses. Second, this study does not directly quantify the change in health insurance plans' incentive for risk selection based on the inclusion of CSHCN information in risk adjustment. Although we show the change in the magnitude of capitation rates, we do not provide a measure of the expected profitability of various selection strategies. One direction for future study is to simulate the incentives under different risk-adjustment models based on alternative enrollment strategies. Anther important direction for future work would be to develop a new risk-adjustment tool based on diagnostic information. Although the HCC model performed relatively well on pediatric populations, we found that only a small proportion of expenditure variation was explained by the HCC model. Finally, given the large amount of unexplained variation that remains after risk adjustment, another important topic in this area would be to study a blend of capitation with fee-for-services, as proposed by Newhouse (1986).

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix SA1: Author Matrix.

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