Predicting High-Cost Pediatric Patients: Derivation and Validation of a Population-Based Model

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ABSTRACT (Word count: 248)

Background: Health care administrators often lack feasible methods to prospectively identify new pediatric patients with high health care needs, precluding the ability to proactively target appropriate population health management programs to these children.

Objective: To develop and validate a predictive model identifying high-cost pediatric patients using parent-reported health (PRH) measures that can be easily collected in clinical and administrative settings.

Design: Retrospective cohort study using 2-year panel data from the 2001-2011 rounds of the Medical Expenditure Panel Survey

Subjects: 24,163 children ages 5-17 with family incomes below 400% of the federal poverty line

Measures: Predictive performance, including the *c* – statistic, sensitivity, specificity, and predictive values, of multivariate logistic regression models predicting top decile health care expenditures over a 1-year period

Results: Seven independent domains of PRH measures were tested for predictive capacity relative to basic sociodemographic information: the Children with Special Health Care Needs (CSHCN) Screener; subjectively rated health status; prior year health care utilization; behavioral problems; asthma diagnosis; access to health care; and parental health status and access to care. The CSHCN screener and prior year utilization domains exhibited the highest incremental predictive gains over the baseline model. A model including sociodemographic characteristics, the CSHCN screener, and prior year utilization had a *c*-statistic of 0.73 (95% CI, 0.70-0.74), surpassing the commonly used threshold to establish sufficient predictive capacity (*c*-statistic > 0.70).

Conclusion: The proposed prediction tool, comprised of a simple series of PRH measures, accurately stratifies pediatric populations by their risk of incurring high health care costs.

INTRODUCTION

The implementation of the Affordable Care Act accelerates a shift in health care delivery away from fee-for-service-driven models towards value-based models.[1] In pediatrics, a hallmark of this movement is an enhanced focus on care coordination and population health management initiatives that provide holistic supports to children and families requiring services spanning a variety of medical and social service providers.[2,3] Indeed, the early detection and management of high-need children will be a critical determinant of the ability of new integrated payment systems (such as Accountable Care Organizations (ACOs)) to improve pediatric health outcomes.[4]

To target high-need children, these initiatives seek to identify children that are likely to be at risk for elevated use of health care services.[5] While traditional risk assessment models used by insurers to identify high-cost children typically rely on historical medical claims,[6] these data may be unavailable for many low- and moderate- income children eligible for Medicaid or subsidized Marketplace coverage who experience high levels of insurance volatility, often referred to as "churn"[7-9] and who may therefore be new to a health insurance plan. Churn is also a challenge for providers, many of whom experience frequent turnover in their low- and moderate- income patient panels due to patient residential instability and changing health insurance networks.[10,11] Accordingly, detailed records documenting expert opinion (e.g. clinical notes) about the child's medical needs are also lacking.

Our objective is to develop and validate a predictive tool comprised of parent-reported health (PRH) measures that could be collected on a routine basis through health plan enrollment or patient intake at a pediatrician's office. PRH alternatives to claims-based risk adjustment methods have been examined on a limited basis in the pediatric literature, focusing on either the predictive ability of one potential domain of interest[12] or multiple domains as a whole.[13] By contrast, one of our main contributions is to assess the incremental predictive capacity of a wide range of PRH domains. To our knowledge, an incremental comparison of survey-based measures has only recently been conducted among low-income adults.[14,15] This approach provides a concrete demonstration of the trade-off between predictive capacity and respondent burden inherent in the implementation of a PRH instrument. As such, it can provide critical guidance to providers and administrators interested in using short-form assessments to maximize their chances of prospectively identifying children likely to use extensive health care resources.

METHODS

Participants

Data were drawn from the Medical Expenditure Panel Survey (MEPS), a population-based survey administered by the Agency for Healthcare Research and Quality (AHRQ) that follows a nationally representative sample of households over 2 calendar years. The MEPS data are uniquely well-designed for high-cost predictive tool development, as they contain consistently collected measures spanning multiple domains of health status, utilization, and expenditures over the 2 year panel study period. The analytic sample was constructed using data on children ages 5-17 from Panels 6-15 of the MEPS, which were conducted during 2001-2011. We exclude children younger than age 5 since certain predictor measures are not available in the MEPS for children ages 0-4.

We restricted our sample to children with family incomes at or below 400 percent of the federal poverty line (FPL) in the first year of the MEPS. Children in families with incomes in this range may be eligible for Medicaid or the Children's Health Insurance Program (CHIP), or qualify for subsidized coverage under the new health insurance exchanges (also known as "the Marketplace"). We focused on this population since high levels of churn are anticipated under the exchanges[7,16] and historically have been a problem under Medicaid and CHIP.[9] After excluding children with missing data, the final analytic sample contained 24,163 children. In all analyses, we used analytic weights provided by AHRQ to provide estimates that are nationally representative of the civilian, non-institutionalized population.

Measures

The selection of predictors was guided by Andersen's behavioral model of health services use, [17,18] which posits that health care utilization is jointly influenced by predisposing factors that affect norms about whether to seek care (e.g. child sex, age, parental education), enabling factors that affect ability to seek care (e.g. health insurance, income), and need-related factors (e.g. perceived health status, presence of a special health care need). Moreover, we focused on predictors that might be feasible for provider groups and/or administrators to collect through short surveys and for which prior studies have demonstrated an association with elevated health care utilization. We identified and tested the performance of measures constructed from parent-reported information from the first year of the MEPS to predict high health care utilization for children during year 2. In keeping with existing research,[13,15,19] we identified children in the highest decile of annual expenditures since these are children who might benefit from additional case management and care coordination. Within our sample, children in the top decile had approximately $2662 (in 2011 dollars) or more in health care expenditures per year (mean = $6657), compared to the overall sample with median expenditures of $269 (mean = $1129).

Our final domains (Table 1) included measures of child health status and special needs, which have been addressed in the literature on pediatric risk adjustment,[12] health care access variables, as well as family factors that may also impact utilization and spending. The baseline set of predictors was a standard set of *sociodemographic characteristics* that are currently collected by many providers or health plans, including: child age in years; sex; family structure (parental marital status, number of adults in family, number of children in family); geographic region; and family income (0-124% FPL, 125-199% FPL, 200-399% FPL). We also included indicators of public or private health insurance coverage during the second year of the MEPS in the baseline set.

Motivated by Yu and Dick's[12] examination of the predictive ability of PRH measures (for the purpose of risk adjusting payments for capitated pediatric insurance plans) we first considered the following 2 PRH domains: the *Children with Special Health Care Needs Screener* (*CSHCN*) and *subjectively rated health status*. The CSHCN screener is a widely used [20-22] measure comprised of five question sequences designed to identify children with increased risk of behavioral, developmental, or health delays who likely require greater than average use of health care services. It has been found to be predictive of elevated use of services in the child population overall, [19,12,23] and more recently among Spanish language children specifically.[24] Children are identified as having a special health care need if the adult respondent reports any of the 5 health care needs and confirms that it is the consequence of a medical, behavioral, or other health condition lasting or expected to last at least 12 months. The areas of special health care need are (1) need or use of prescription medications; (2) an above routine use of services; (3) need or use of specialized therapies or services; (4) need or use of mental health counseling; and (5) a functional limitation. Under this domain, we included an indicator for the presence of at least one special health care need, as well as indicators for each of the 5 types of special health care needs.

S*ubjectively rated health status* was measured using 5 categorical variables indicating parents' perceptions of the child's general health status and mental health status, as well as information on whether the child seems less healthy than other children, has never been seriously ill, and usually catches whatever is going around. Subjectively rated health status is widely collected and reported and has been found to be associated with membership in the top expenditure decile among children.[19]

Moving beyond the PRH specifications explored in Yu and Dick, we tested the predictive capacity of the child's *prior health care utilization.* We included 3 measures of utilization that indicated whether the child had at least 1 visit to the emergency room, 1 or more inpatient hospital stays, and 10 or more office-based provider visits during the first year of the MEPS. Similar measures have been found to be highly predictive of health care expenditures among the low-income adult population.[15]

We also used the Columbia Impairment Scale as a measure of *child behavioral problems*, in recognition of the high costs associated with pediatric behavioral health issues.[25] The Columbia Impairment Scale is a 13-item scale that measures psychiatric impairment among school-age children and adolescents. For each item, a knowledgeable adult rated whether a child experienced problems in common situations, activities, or settings on a 4-point scale. The Columbia Impairment Scale has been validated within a culturally diverse community sample where it demonstrated high correspondence with clinician ratings of psychiatric impairment.[26]

We assessed the presence of a parent-reported *asthma diagnosis* as a potential predictor since pediatric disease management efforts often center around asthma initiatives.[27,28] PRH screeners currently used by managed care organizations typically screen for asthma.[29]

We considered three measures of *access to health care*. These measures included having a usual source of care (other than the emergency room) in year 1, experiencing any periods without health insurance in year 1, and having more than one source of health insurance coverage in year 1 (representing a shift from public to private coverage, for example). Children that have less than a full year of enrollment in Medicaid display different expenditure patterns than those enrolled for a full year[19] and children lacking a usual source of care utilize fewer services.[30] There is also some concern regarding reduced access associated with transitions between public and private insurance.[31]

Finally, we considered measures of *parental health status and access*. Parental health status and access is independently of interest because providers and health plans may increasingly consider the health needs of all members of a family enrolling in a health plan, additionally there is some literature suggesting that parental health status influences use of services for children.[32] Measures included the physical and mental health status of the child's mother, or if the child did not reside with the mother, the health status of the knowledgeable respondent (usually a father or grandparent) reporting on the child's health. The mother was chosen as a primary respondent because more children in the MEPS reside with a mother, and mothers are often important decision-makers in children's utilization of health services. We also included whether the mother (or other adult) had a usual source of care, which may also predict service use of a child,[30] and the parent's health insurance status in year 1.

Statistical Analysis

We tested a series of models that added each domain of PRH predictors to a standard set of baseline characteristics to predict the probability of membership in the highest expenditure decile. To avoid overfitting, model performance was assessed using a split-sample approach that divides the analytic sample into two equally sized (i.e. 50-50 split) separate, randomly selected subsamples for model building and testing. After each model was fit using the first subsample, the resulting parameter estimates were applied to the second subsample to test model performance. All models were estimated using multivariate logistic regression.

To assess the performance of each model, we measured model discrimination using the *c*-statistic, which is the most commonly reported measure of model discrimination. For a dichotomous outcome, it corresponds to the area under the receiver operating characteristic curve, a plot of the sensitivity (true positive rate) against 1-specificity (false positive rate) across the entire range of possible predicted probability thresholds.[33-35] The c-statistic ranges between 0.5 and 1, with a value of 0.5 reflecting predictive ability no more accurate than a coin flip and a value of 1 reflecting perfect predictive ability. We calculated differences in the *c*-statistic between each new model and the baseline model to determine the incremental gain in predictive performance. In keeping with the related literature,[14,15] we used a 500 replicate bootstrap procedure to compute confidence intervals for the *c*-statistic for each model, as well as to determine the statistical significance of any improvements relative to the baseline model.

After determining the best-performing domains of predictor variables, we examined the predictive performance of a model inclusive of each of these domains. We also considered a "kitchen-sink" model that included all domains of predictors. For the top-performing and all-inclusive models, we further evaluated performance with measures of sensitivity, specificity, positive predictive value (percentage of predicted top expenditure decile sample members who are classified correctly), and negative predictive value (percentage of predicted non-top expenditure decile sample members who are classified correctly) using a range of cut-points (50th, 75th, and 90th) for the predicted probability of top-decile expenditures.

All analyses were performed using Stata version 13.1 (SE Version 13 [StataCorp, College Station, TX]).

RESULTS

Sample Characteristics

Table 2 presents descriptive statistics for the 24,163 members in the combined model building and testing subsamples, as well as for the subset of children (*n* = 2,304) with expenditures in the top decile. Parent reports of child health status indicated that children with high expenditures had worse physical and mental health compared to the full sample of children, while measures of special health care needs revealed greater needs for prescription drugs, medical care, and other types of care. Higher proportions of children in the top decile had possible behavioral impairments and asthma diagnoses than children in the full sample. Accompanying these differences in measures of health, parents reported greater interaction with the health care system among children in the top decile. Prior health care utilization, as measured by any ER visit, inpatient discharge, or 10 or more health care visits during the first year of the MEPS, was higher among children with top expenditures.

Multivariate Analysis

We first examined the incremental performance of each domain of predictor variables when added to our baseline model. Table 3 reports measures of model discrimination for the baseline model (Model 1) and each augmented model (Models 2-8). The *c*-statistic for the baseline model was 0.62 (95% confidence interval [CI], 0.60-0.64), which falls below the general guideline for model acceptability of 0.70.[36] Almost all augmented models offer a statistically significant improvement in the *c*-statistic over this baseline. The two largest improvements accompanied the addition of the CSHCN (Model 2) and prior health care utilization (Model 4) measures, in that order. The highest performing model (Model 2) exhibited a *c*-statistic of 0.72 (95% CI, 0.70-0.74).

Next, we examined a model that included the two top-performing domains – CSHCN and prior utilization (Model 9), as well as a model inclusive of all predictor domains (Model 10). The *c*-statistics for Models 9 and 10 were roughly equivalent with Model 9 performing slightly better with a *c*-statistic of 0.73 (95% CI, 0.70-0.74). The *c*-statistics for both models exceeded those of all prior models.

To further evaluate the best-performing models (Models 2, 4, 9, and 10), Table 4 provides information on the sensitivity, specificity, and positive and negative predicted values under each model for cut-points equivalent to the 50th, 75th, and 90th percentiles of the predicted probabilities of top-decile expenditures. All models showed improvements on these measures when compared to the baseline model. Models 9 and 10 performed the best with the preferred model depending on the cutoff of predicted probability, or risk threshold, in use. Importantly, there is a marked trade-off between sensitivity and specificity associated with differing values of the risk threshold. Accordingly, administrators must weigh their tolerance for false positives relative to false negatives when choosing a cutoff. In a supplemental appendix, we provide a sample screening tool and instructions for scoring risk among pediatric patients for providers and payers interested in implementing our prediction algorithm.

DISCUSSION

To our knowledge, this paper is the first to develop and validate a population-level predictive standard for identifying high-cost pediatric patients using easy-to-collect PRH measures. Our study finds that the CSHCN instrument in combination with prior year's health care utilization is highly predictive of future year's expenditures; indeed, the combination of the 2 domains performs on par with a model including the universe of all proposed domains. Importantly, our findings suggest that these 2 domains can jointly serve as a low-cost, easily administered screening tool for payers and providers. Reassuringly, this tool is unlikely to be overly burdensome for respondents; existing work finds that the CSHCN instrument takes only 1 minute for a parent to complete,[20] and the prior year utilization domain is populated by 3 simple questions.

Several limitations warrant consideration. First, excepting asthma, we were unable to explore measures indicating the presence of specific health conditions, a domain that exhibits considerable predictive capacity among adult populations.[14,15,37] While traditional ICD-based disease classifications (such as those available in the MEPS) are poor predictors of pediatric costs,[35,38] newer condition classifications, such as those included in the National Survey of Children's Health, [39] are promising and deserve future inquiry. Additionally, it is important to keep in mind that, in keeping with its claims-based counterparts, a PRH screening tool is likely to exhibit low positive predictive value. An important implication is that predictive models are best deployed as a first screen, complemented by follow-up contact from a case manager and, where appropriate, a comprehensive intake and history from a clinician.

Finally, our study only identifies those children with critical health needs that lead to elevated use of health services over the short-term. There are likely to be some children with poor access to health care who would benefit from case management and other medical interventions in order to address emerging health concerns (such as undiagnosed asthma exacerbated by unstable family circumstances). While these concerns may ultimately lead to future health expenditures, they are not always apparent over a 1-year period. Accordingly, we recommend balancing the use of the PRH instrument with other instruments designed to screen for material deprivation and social or family stressors.[40-43]

Despite these limitations, the findings of our paper compellingly indicate that PRH measures can be used to identify high-utilizers among pediatric populations. The predictive performance of our model including the CSHCN screener and the prior year utilization domains (c = 0.73) is similar to a parsimonious screener for identifying likely high-cost cases among adults (c = 0.75).[14,15] As a benchmark, these c-statistics approach, but do not quite meet, those of the Framingham Heart study (c = 0.77 for overall study population, ranging from 0.63-0.86 across different ethnic groups),[44,45] which is among the most frequently used clinical prediction rules. Moreover, our model demonstrates similar sensitivity, specificity, and predictive values as a considerably longer instrument designed to identify high-cost pediatric patients (no c-statistic available).[13]

As mentioned above, the availability of an easy-to-administer risk assessment tool is especially relevant for low-income pediatric populations, who experience higher levels of churn relative to their higher-income peers and as a result are less likely to have a stable claims history.[46] As such, we believe that some of the most important clinical applications pertain to Medicaid providers and insurers serving poor and near-poor children. For example, risk scores derived from a simple PRH tool could help inform the design of care plans for new (or returning) enrollees in Medicaid-serving managed care organizations providing primary care case management (PCCM) services. State Medicaid agencies could also use a PRH tool to help determine eligibility for targeted case management. Finally, as exemplified by Illinois' current guidelines for Medicaid ACOs,[47] Medicaid agencies could encourage coordinated care entities and other safety net providers to implement risk screens for new and returning patients to ensure that high-need pediatric members are quickly connected with needed services.

Beyond using a screening tool to target case management and care improvement programs, identifying which children are at greater risk for elevated health care expenditures can be useful for program planning and financing purposes. In particular, our non-proprietary risk screening tool can be used by state Medicaid programs to ensure that there is an appropriate balance of risk across different Medicaid managed care plans, and to counteract any risk selection behavior by insurers (also known as "cream-skimming").

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Table 1. Domains of Predictors

Domain	Measures	Adapted from
1) Baseline characteristics	Age Sex Parental marital status Number of adults in family Number of children in family Geographic region Family income Health insurance coverage	Kuhlthau et al. 2004
2) Presence of special health care need	Children with Special Health Care Needs (CSHCN) screener	Bethell et al. 2002
3) Subjectively rated health status	Perceived general health Perceived mental health Child less healthy than others Child has never been seriously ill Child usually catches whatever is going around	Yu and Dick 2010
4) Prior health care utilization	Emergency room care Inpatient hospital stays 10+ health care visits	Wherry et al. 2014
5) Behavioral problems	Columbia impairment scale	Bird et al. 1996
6) Asthma diagnosis	Child ever diagnosed with asthma	Soni 2011
7) Access to health care	Usual source of care Periods without health insurance Coverage transitions	Birken and Mayer 2009; Buchmueller, Orzol, Shore-Sheppard 2014
8) Parental health status and access	Perceived maternal general health status Perceived maternal mental health status Mother has usual source of care Mother's health insurance status	Minkovitz et al. 2002; Minkovitz et al. 2005

Table 2. Descriptive Statistics for Analytic Sample from MEPS Panels 6-15: Children Ages 5-17 with Incomes Below 400% FPL

%unless otherwise stated	Full sample *N* = 24 163	Top expenditure decile *N* = 2 304
1) Baseline characteristics (administrative data)		
Age in years, mean (SD)	11.08 (4.24)	11.78 (3.64)
Gender, male	51.05	51.50
Number of adults in family, mean (SD)	1.92 (0.92)	1.88 (0.77)
Number of children in family, mean (SD)	2.52 (1.47)	2.27 (1.19)
Married parent family	67.53	68.84
Income (% FPL)		
0-124%	31.29	23.11
125-199%	22.10	19.11
200-399%	46.61	57.78
Region		
Northeast	15.82	18.45
Midwest	21.42	24.23
South	37.90	36.86
West	24.86	20.46
Insurance status		
Any private insurance	54.25	63.40
Public insurance	37.22	32.35
Uninsured	8.53	4.25
2) Special health care needs		
Has a special health care need	21.74	48.76
Needs or uses prescription drugs	15.77	39.76
Needs or uses more medical care	9.06	27.60
Has a limitation	5.31	15.69
Needs or uses special therapy	4.08	11.35
Needs or uses counseling	7.27	20.42
3) Subjectively rated health status (mean (SD))		
Perceived health status*	1.75 (0.99)	1.98 (1.02)
Perceived mental health status*	1.73 (1.01)	1.99 (1.06)
Child less healthy than other children^	4.58 (1.05)	4.25 (1.27)
Child has never been seriously ill^	1.97 (1.75)	2.31 (1.69)
Child usually catches what is going around^	3.75 (1.52)	3.52 (1.42)
4) Prior health care utilization		
Any ER visits	11.33	16.50
Any inpatient discharges	1.75	5.05
10+ health care visits	4.30	18.24
5) Child behavioral problems		
Columbia Impairment Scale score >=15	12.71	22.89
6) Asthma diagnosis		
Ever diagnosed with asthma	11.98	21.83

Table 2. Descriptive Statistics for Analytic Sample from MEPS Panels 6-15: Children Ages 5-17 with Incomes Below 400% FPL, *continued*

%unless otherwise stated	Full sample *N* = 24 163	Top expenditure decile *N* = 2 304
7) Access to health care		
Usual source of care	87.06	92.57
Periods without insurance coverage	8.96	4.91
Transitions in insurance coverage	7.03	8.11
8) Parental health status and access (mean (SD))		
Perceived health status*	2.41 (1.19)	2.48 (1.10)
Perceived mental health status*	2.10 (1.13)	2.19 (1.05)
Usual source of care	75.77	84.24
Health insurance coverage	79.14	85.98
9) Outcome		
Expenditures in 2011 dollars, mean (SD)	1,129.71 (4,246.12)	6,656.59 (9,252.31)

Medical expenditures presented in 2011 dollars using the GDP price index as recommended by AHRQ.
* 1=excellent, 2=very good, 3=good, 4=fair, 5=poor
^ 1=definitely true, 2=mostly true, 3=don't know, 4=mostly false, 5=definitely false

Table 3. Comparison of Top-Expenditure Models for Pediatric Population

		c -statistic	diff.
Model 1:	Baseline	0.620	---
		(0.597, 0.641)	
Model 2:	Baseline + CSHCN	0.717	0.096**
		(0.696, 0.739)	(0.077, 0.118)
Model 3:	Baseline + health status	0.672	0.051**
		(0.651, 0.692)	(0.034, 0.070)
Model 4:	Baseline + prior utilization	0.689	0.069**
		(0.669, 0.710)	(0.055, 0.085)
Model 5:	Baseline + behavior problems	0.644	0.024**
		(0.624, 0.664)	(0.011, 0.037)
Model 6:	Baseline + asthma diagnosis	0.646	0.025**
		(0.624, 0.668)	(0.013, 0.040)
Model 7:	Baseline + access	0.629	0.008*
		(0.609, 0.649)	(0.001, 0.016)
Model 8:	Baseline + parent health and utilization	0.633	0.013**
		(0.612, 0.652)	(0.004, 0.021)
Model 9:	Baseline + CSHCN + prior utilization	0.731	0.111**
		(0.699, 0.737)	(0.077, 0.116)
Model 10:	Baseline + all domains	0.730	0.110**
		(0.711, 0.751)	(0.089, 0.133)

N = 12 101 for validation sample. 95% confidence intervals in paretheses.* indicates significant difference from baseline model at $p < 0.05$; ** indicates significant difference from base model at $p < 0.01$.

Table 4. Sensitivity, Specificity, Positive and Negative Predictive Values by Risk Threshold

	High Cost		
	50th percentile	75th percentile	90th percentile
Model 1: Baseline			
Predicted probability of high expenditures	0.089	0.121	0.146
Sensitivity	0.661	0.377	0.141
Specificity	0.519	0.765	0.905
Positive predictive value	0.139	0.158	0.149
Negative predictive value	0.929	0.912	0.900
Model 2: Baseline + CSHCN			
Predicted probability of high expenditures	0.064	0.010	0.223
Sensitivity	0.755	0.516	0.311
Specificity	0.530	0.781	0.925
Positive Predictive Value	0.159	0.217	0.327
Negative Predictive Value	0.948	0.932	0.919
Model 4: Baseline + prior utilization			
Predicted probability of high expenditures	0.077	0.106	0.131
Sensitivity	0.721	0.473	0.291
Specificity	0.526	0.776	0.922
Positive Predictive Value	0.152	0.199	0.307
Negative Predictive Value	0.941	0.926	0.917
Model 9: Baseline + CSHCN + prior utilization			
Predicted probability of high expenditures	0.062	0.095	0.211
Sensitivity	0.763	0.539	0.338
Specificity	0.531	0.784	0.928
Positive Predictive Value	0.160	0.227	0.356
Negative Predictive Value	0.950	0.935	0.927
Model 10: Baseline + all domains			
Predicted probability of high expenditures	0.062	0.099	0.209
Sensitivity	0.768	0.535	0.339
Specificity	0.532	0.783	0.928
Positive Predictive Value	0.162	0.225	0.357
Negative Predictive Value	0.951	0.936	0.923

Note: Risk threshold refers to the cutoff in predicted probability (50th, 75th, or 90th percentile) used to predict the outcome.

SUPPLEMENTARY APPENDICES

Appendix A. Sample Screener

Below is sample screener that may be used to construct the predictor measures included in the top performing PRH domains in our paper. The CSHCN Screener is based on Bethell et al. (2002), while the remaining questions were adapted from the 2008 National Health Interview Survey.

<u>Children with Special Health Care Needs Screener</u>

1. Does (CHILD) currently need or use medicine prescribed by a doctor, other than vitamins?
    a. [If answered YES to question 1] Is this because of any medical, behavioral or other health condition?
    b. [If answered YES to question 1] Is this a condition that has lasted or is expected to last for at least 12 months?
2. Does (CHILD) need or use more medical care, mental health or educational services than is usual for most children of the same age?
    a. [If answered YES to question 2] Is this because of any medical, behavioral or other health condition?
    b. [If answered YES to question 2] Is this a condition that has lasted or is expected to last for at least 12 months?
3. Is (CHILD) limited or prevented in any way in (his/her) ability to do the things most children of the same age can do?
    a. [If answered YES to question 3] Is this because of any medical, behavioral or other health condition?
    b. [If answered YES to question 3] Is this a condition that has lasted or is expected to last for at least 12 months?
4. Does (CHILD) need or get special therapy such as physical, occupational or speech therapy?
    a. [If answered YES to question 4] Is this because of any medical, behavioral or other health condition?
    b. [If answered YES to question 4] Is this a condition that has lasted or is expected to last for at least 12 months?
5. Does (CHILD) have any kind of emotional, developmental or behavioral problem for which (he/she) needs or gets treatment or counseling?
    a. [If answered YES to question 5] Is this a condition that has lasted or is expected to last for at least 12 months?

Notes: Children with positive responses to any of the five main questions and its corresponding follow-up questions meets the criteria of having a special health care need. For more information on the CSHCN Screener, see Bethell et al. (2002).

Prior Health Care Utilization

1. During the past 12 months, has (CHILD) gone to a hospital emergency room about his/her health (This includes emergency room visits that resulted in a hospital admission.)?
2. Was (CHILD) hospitalized in the past 12 months? Do not include a stay in the emergency room.
3. During the past 12 months did (CHILD) receive care from doctors or other health care professionals 10 or more times? (Do not include telephone calls.)

Appendix B. Formula for Estimating Risk Score

This is a tool designed for predicting whether a child is likely to incur elevated health care expenditures (defined as being in the top 10% of all spenders). The tool was created by Leininger, Saloner, and Wherry to estimate the probability of top spending over a 12-month period among the pediatric population (ages 5-17) with family incomes less than 400% FPL. Please see the paper for additional technical details about the development of the risk model.

To calculate the probability that a child is at risk for expenditures in the top decile first, fill in patient values for each explanatory variable in column 2 in the worksheet below. Next, multiply column 1 and column 2 and write the value in column 3. Add together all the values of column 3 to calculate the raw risk score. The raw risk score (*y)* can be placed into the following equation to calculate the predicted probability.

$$P_{high\ cost} = \frac{e^{y}}{1 + e^{y}}$$

In a national sample, a P greater than or equal to 0.095 indicated high risk and a P greater than or equal to 0.211 indicated very high risk of elevated health care spending. Table 4 in the main text of the paper presents the tradeoffs in sensitivity, specificity, and predictive value with using these scores, which represented the 75th and 90th percentiles of predicted probabilities, respectively.

Worksheet for calculating raw risk score:

Explanatory variable	Parameter estimate (1)	Patient value (2)	Product: (1) x (2)
Constant	-4.059	1	-4.059
Has a special health care need*	0.153		
Needs or uses prescription drugs*	0.965		
Needs or uses more medical care*	0.407		
Has a limitation*	0.339		
Needs or uses special therapy*	0.408		
Needs or uses counseling*	0.226		
Any ER visits in past year*	0.149		
Any inpatient discharges in past year*	0.977		
10+ health care visits in past year*	1.251		
Age (in years)	0.215		
Age ^ 2	-0.007		
Male gender*	-0.171		
Number of adults in family	-0.039		
Number of children in family	-0.132		
Married parent family*	0.09		
Family income is 125-199% FPL*	0.232		
Family income is 200-399% FPL*	0.481		

Midwest region*	0.064	
South region*	-0.066	
West region*	-0.152	
Currently has public health insurance*	-0.178	
Currently uninsured*	-0.493	
Total raw risk score		

Note: An asterisk following an explanatory variable indicates that a value of 1 should be recorded in column 2 if the characteristic accurately describes the patient. Otherwise, a value of 0 should be recorded.