IV

Analysis of High-Cost Cases

A. Background

The data we reviewed indicate that, while only 1% of claimants have expenditures above $25,000 in any given year, these individuals account for more than 25% of claim costs. Thus, any analysis of risk assessment and risk adjustment must pay special attention to these large claims. If the goal of risk adjustment in the public policy sense is to motivate carriers to be efficient, as opposed to motivating carriers to select the best risks, then finding a solution to the problem of compensating carriers fairly for these high-cost claimants is an absolute necessity.

Reinsurance is one traditional method for dealing with these high-cost claims. But the incentives it generates may create perverse incentives. Generally, a reinsurance system for risk adjustment would need to be mandatory for all participating carriers. The reinsurance premium would then be derived from the expected cost of all the high-cost claims within the system. If efficient managed care organizations as well as inefficient indemnity carriers are participating, the more efficient carriers end up subsidizing the inefficient ones through the reinsurance premium since payment is based on actual claim dollars paid, and the less efficient carriers are in effect rewarded for their higher claims. More efficient health plans also have fewer cases which exceed the reinsurance limits. Thus, this system does not reward better management of care.

The alternative that has perhaps received the most attention is that exemplified by the New York high-cost condition and California HIPC methods. Instead of paying carriers for high-cost cases on the basis of actual claims, payments are based on the occurrence of specific high-cost diagnoses or procedures and fixed in advance. Thus a plan with an enrollee who is diagnosed with myeloid leukemia might receive a predetermined payment of, say, $120,000. Since the payment is known in advance to the carrier, the carrier's incentive is to provide efficient care. At the same time, if the plan knows that it will be compensated for having a disproportionate number of high-cost enrollees, its incentives for risk selection, and the consequences of adverse selection, are reduced.

None of the methods we have tested so far pay particular attention to the prediction of expenditures for high-cost cases. Although some DCG models make a distinction for inpatient diagnoses, and should thus capture most high-cost cases, they aggregate together many clinically distinct diagnoses that may have somewhat different expenditures on average. Additionally, the analyses described in Chapter III are all based on data truncated at $25,000, essentially assuming some form of reinsurance system for claims above that amount. We sought to investigate alternative methods for assessing the risk of these high-cost cases.

We explored the potential of a method focused on high-cost conditions to improve on age and sex and the ADG models. Since many higher-cost hospitalizations were modeled explicitly under the DCG method, we did not explore the addition of our conditions to these models. Instead, we evaluated our results in relation to the PIPDCG and EDCGDX models.

The large amount of data available to us for this study provided an opportunity for a new analysis of high-cost diagnoses. We followed the approach that the HIPC took in developing its list of marker diagnoses, as described in Chapter II (HIPC, 1995). The HIPC list includes groupings of diagnoses that, when associated with a hospitalization, tend to generate costs in excess of $15,000, and that also meet various clinical criteria: (1) the assignment of the diagnosis must be relatively nondiscretionary; (2) the decision to hospitalize must also be relatively nondiscretionary; (3) careful ambulatory management will not necessarily be sufficient to prevent hospitalization; and (4) the condition must have some degree of chronicity to it, so that a plan could select against individuals with that diagnosis. The lists of diagnoses and procedures that New York State and Kentucky use in their high-cost risk adjustment mechanisms

are quite short (the New York list accounts for less than 5% of expenditures over $25,000) and research is currently under way to extend them. Thus a list comparable to the HIPC list seemed more likely to indicate the potential of a high-cost condition-based method.

We initially considered the use of the HIPC list itself in testing a high-cost condition approach. Due to the more limited amount of data available to the HIPC, however, certain high-cost diagnoses (several types of cancer, in particular) did not emerge as HIPC marker diagnoses. We constructed an alternative list, based on our own data. We relied on our clinical consultant's judgment to approximate the diagnosis screening process that the HIPC undertook. We also compared our list with the HIPC diagnoses to confirm our selections.

B. Methods: Development of an Alternative List of High-Cost Diagnoses

1. Initial List of Diagnoses

We identified high-cost diagnoses using a combined data set from pools representing approximately 80% of all observations eventually used in the study, or more than 3 million records. Since our initial analysis showed that 95% of all enrollees with expenditures over $25,000 had one or more hospital admissions, we only used data for enrollees with an inpatient episode in a year to develop our list.[1] Unlike in the HIPC process, we were unable to use secondary inpatient diagnoses, because these were not recorded in our data.

We first summarized statistically total expenditures per enrollee for all inpatient diagnoses. To simplify the analysis, we did this separately at the three-, four-, and five-digit level of coding.[2] Beginning with the four-digit list, we then identified diagnoses which met the following conditions:

- A four-digit diagnosis code had to appear at least 10 times in our data as the *only* principal inpatient diagnosis; individuals with more than one principal inpatient diagnosis (thus necessarily more than one hospitalization) were not used for development of the list.[3]
- Mean expenditures for these occurrences had to be $25,000 or above.
- Assignment of the diagnosis and the decision to hospitalize are relatively nondiscretionary.
- For this diagnosis, hospitalizations cannot always be prevented through proper medical management.
- The condition is one that plans could conceivably select against.

To be specific, our clinician assigned a score of 1 to 3 indicating how discretionary assignment of the diagnosis and hospitalization are, how preventable hospitalizations are, and how likely it is that a plan could systematically avoid enrollees with the condition. In each case, a lower score indicated lower discretion or potential for gaming. Any diagnosis with a score of 3 on any dimension was excluded, and any diagnosis with more than one score of 2 was also excluded. We did not exclude any cancers.

The above procedure was applied to all four-digit codes for which mean expenditures were above $25,000 and which showed a frequency of 10 or above in our combined data set. We also considered whether any five-digit codes should be broken out. Because not all insurers record ICD9 codes at the five-digit level, and because we wanted to avoid making the list unduly complex, we decided to set a higher threshold of frequency for five-digit codes, requiring that they occur at least 50 times in the data. We then included a specific five-digit code in the list only if:

- It represented an acceptable condition according to the same criteria as applied to the four-digit codes
- Its distribution was significantly different from the distribution of expenditures for the corresponding four-digit code.

In addition, initial episodes of care were excluded. These criteria turned out to be stringent enough that only one five-digit code was added to the list, 51881, respiratory failure. Finally, we added three-digit codes with frequencies of 10 or above and mean costs above $25,000 that were not excluded by our criteria and that appeared on the HIPC list.

2. Grouping and Elimination of Diagnosis Codes

Codes were then grouped according to clinical relatedness and relative homogeneity of cost distributions. In order to increase the likelihood that the final groups truly represent high-cost conditions, groups were kept on the list under either one of two sets of conditions: (1) the code(s) in the group met the clinical criteria indicated above, and the group appeared on the list developed by HIPC; or (2) the group had a total of 50 or more cases, or, failing that, a median cost greater than $50,000. Thus we interpreted appearance of the

group on the California list as confirmation of our clinical analysis, and indication that the condition probably was of greater significance generally than our sample may have suggested. Clinically isolated diagnoses of low frequency or generally lower cost that met our clinical criteria but were not identified on the California list were not kept on the list.

Table 23 shows the 43 groups that were obtained in this way, together with statistics describing the distribution of expenditures for each diagnosis code included. As shown, the list encompasses 52 three-digit codes, 22 four-digit codes, and one five-digit code.[4] Together these codes account for 35% of expenditures in our sample over $25,000, or about 9% of all expenditures. Only 5% of all individuals with one or more of these conditions had two or more. Only 0.3% had three or more. Table 24 shows the percentage of total expenditures over $25,000 each group accounts for, as well as the incidence of each group in our sample. As shown, although these conditions are costly, many are also infrequent.

C. Methods: Evaluation of the List of Marker Diagnoses

We combined the new list of marker diagnoses with two risk assessment models evaluated previously (see Chapter III): age and sex alone, and ADGs combined with age and sex. This involved adding 43 dummy variables to each of these two models, one dummy variable for each of the conditions shown in Table 24. Individuals with no principal inpatient diagnosis in any one of the 43 groups have a 0 value for each of the 43 dummy variables. Individuals with only one or more principal inpatient diagnoses belonging to a single group have the dummy variable for that group set to one. We treated individuals with multiple principal inpatient diagnoses, belonging to two or more different groups,[5] in two ways:

(1) After having ranked the groups according to their mean expenditures, we assigned each such individual to the group corresponding to the most expensive principal inpatient diagnosis.
(2) We set as many of the group dummy variables equal to one as there were principal inpatient diagnoses belonging to different groups.

For example, under the first method, an individual with one principal inpatient diagnosis of 150 (malignant neoplasm of esophagus) and another (associated with another admission during the same year) of 431 (intracerebral hemorrhage), would be assigned to the group "Malignant neoplasm of the esophagus" because mean expenditures for persons in that group are $71,000, higher than the $56,000 for persons in the group "Intracerebral hemorrhage." Under the second method, the same individual would be assigned to *both* groups.

The first method for treating individuals with multiple principal inpatient diagnoses parallels the DCG approach of assigning individuals to their highest DCG. Relative to the second method, it may reduce incentives for any clinically unnecessary hospitalizations, and it is somewhat simpler. The second method yields higher predicted expenditures for individuals with principal inpatient diagnoses belonging to two or more groups, relative to individuals with diagnoses in only one group. Such individuals are likely to have suffered from one or more significant comorbidities during each hospital stay. Combining each of these two high-cost models with age and sex and ADGs yields four models, which we refer to as: age-sex with principal high-cost conditions (first method), age-sex with all conditions (second method), ADGs with principal high-cost condition, and ADGs with all conditions. These four models are compared to age and sex alone, ADGs alone, PIPDCGs, and EDCGDXs.

We estimated these eight models retrospectively using 1992 data for seven selected pools comprising 850,000 enrollees. To remove any systematic differences by pool, we included a dummy variable for each of the seven pools. Each coefficient for the variables describing the high-cost conditions in the model represents the average additional annual cost across all seven pools of enrollees produced by the described condition. Using the estimated coefficients, we compared the predicted expenditures with actual amounts.[6] Expenditures were not truncated, since our goal was to compare the ability of different models to predict extreme expenditures.

Finally, we compared the predictive accuracy of the models for individuals as well as groups. We did this using the same measures as described in Chapter III.

D. Results

Table 25 reports the predictive accuracy for the eight models tested; the adjusted R^2s are also compared graphically in Figure 13. The PIPDCG and EDCGDX models perform best overall, both with an adjusted R^2 of 0.27 and with very similar values on other measures of predictive accuracy. The two high-cost models combined

TABLE 23
STATISTICAL SUMMARY OF TOTAL ANNUAL HEALTH EXPENDITURES FOR HIGH-COST CONDITIONS IDENTIFIED FOR STUDY, DATA USED FOR IDENTIFYING CONDITIONS—INDIVIDUALS WITH ONE INPATIENT ADMISSION FOR THE YEAR

Inpatient ICD9 Diagnosis*	Description	No. of Cases	Total Health Expenditures						
			Mean Cost	Std Dev.	Mini-mum	25th Pcntl.	Median	75th Pcntl.	Maxi-mum
	AIDS (20)								
0449	HIV Infection, Unspecified	10	54,877	50,698	5,533	17,070	30,546	72,496	140,877
0429	AIDS, Unspecified	12	31,317	17,068	7,689	14,524	34,584	44,286	60,463
	Cancers of the Brain, Respiratory and Digestive Systems, Except Esophagus (19)								
191	Malig Neopl of Brain	98	39,854	28,911	1,927	16,414	34,424	52,316	155,867
141	Malig Neopl of Tongue	17	40,458	27,089	3,761	17,852	39,515	52,278	97,622
151	Malig Neopl of Stomach	22	39,369	29,941	5,132	22,092	38,017	49,877	143,948
152	Malig Neopl of Small Intest, Including Duodenum	13	29,740	25,650	4,791	18,013	24,254	38,075	102,849
153	Malig Neopl of Colon	222	30,608	18,107	2,810	18,609	25,634	38,762	95,776
154	Malig Neopl of Rectum, Rectosigmoid Junction, & Anus	136	46,034	31,939	8,047	26,845	37,972	52,132	184,387
155	Malig Neopl of Liver & Intrahepatic Bile Ducts	24	52,433	29,923	11,163	27,940	50,659	72,320	132,044
157	Malig Neopl of Pancreas	42	42,674	24,459	5,766	23,911	38,292	59,342	107,166
160	Malig Neopl of Nasal Cavities, Middle Ear, & Accessory Sinus	10	35,064	20,267	9,406	13,049	38,974	47,169	73,365
161	Malig Neopl of Larynx	21	38,142	17,506	13,507	31,047	34,653	38,256	77,144
162	Malig Neopl of Trachea, Bronchus, & Lung	269	40,630	30,890	5,108	22,654	33,352	52,062	202,392
164	Malig Neopl of Thumus, Heart, & Mediastinum	10	31,629	19,866	11,052	18,004	24,692	46,301	77,829
189	Malig Neopl of Kidney & OTR & Unspecif Urinary Organs	102	44,738	97,944	6,985	16,839	25,287	38,076	735,401
	Cancer of the Esophagus (6)								
150	Malig Neopl of Esophagus	18	71,046	33,608	10,270	46,688	66,027	97,655	142,746
	Cancers of Bone, Cartilage, Connective and Other Soft Tissue (13)								
170	Malig Neopl of Bone & Articular Cartilage	38	43,264	40,546	4,114	11,497	29,438	64,326	174,119
171	Malig Neopl of Connective & OTR Soft Tiss	34	62,481	83,092	7,941	22,265	31,645	54,902	344,552
	Other Skin Cancer (35)								
173	OTR Malig Neopl of Skin	28	29,460	23,863	2,463	12,786	25,608	37,706	99,241
	Cancers of the Reproductive Systems (Male and Female)(42)								
174	Malig Neopl of Female Breast	1,016	25,235	22,939	3,018	14,172	20,311	29,393	312,145
180	Malig Neopl of Cervix Uteri	98	25,831	16,528	3,132	13,682	22,883	33,968	115,442
183	Malig Neopl of Ovary & OTR Uterine Adnexa	104	33,121	27,365	2,395	15,987	23,685	38,585	177,214
184	Malig Neopl of OTR & Unspecif Female Genital Organs	13	25,001	19,299	12,322	13,062	16,198	22,293	65,668
185	Malig Neopl of Prostate	391	27,463	12,067	4,069	19,314	25,303	32,258	80,698

*Where a three- or four-digit diagnosis code is specified, all four- and five-digit codes below the listed code are included. For example, the three-digit code 195 includes ICD9 codes 195.00 through 195.99. (Number in parentheses to right of condition is the condition i.d.)

TABLE 23—*Continued*

STATISTICAL SUMMARY OF TOTAL ANNUAL HEALTH EXPENDITURES FOR HIGH-COST CONDITIONS IDENTIFIED FOR STUDY, DATA USED FOR IDENTIFYING CONDITIONS—INDIVIDUALS WITH ONE INPATIENT ADMISSION FOR THE YEAR

Inpatient ICD9 Diagnosis*	Description	No. of Cases	Total Health Expenditures						
			Mean Cost	Std Dev.	Mini-mum	25th Pcntl.	Median	75th Pcntl.	Maxi-mum
	Cancers of Other, Ill-defined or Unspecified Sites (36)								
195	Malig Neopl of OTR & Ill-defined Sites	26	28,164	19,906	5,456	15,761	25,347	36,633	105,739
199	Malig Neopl without Specification of Site	36	28,279	22,530	1,385	13,388	19,687	39,538	76,551
	Secondary Cancers (23)								
196	Secondary & Unspecif Malig Neopl of Lymph Nodes	37	30,425	15,309	3,303	20,135	26,241	39,176	67,561
197	Secondary Malig Neopl of Respir & Digestive Systems	99	37,705	41,603	1,794	18,024	29,445	44,041	290,811
198	Secondary Malig Neopl of OTR Specif Sites	120	39,530	29,718	3,662	18,748	34,868	52,623	199,682
	Lymphosarcoma and Reticulosarcoma (14)								
200	Lymphosarcoma & Reticulosarcoma	15	51,979	42,655	12,977	30,514	48,742	59,992	196,272
	Hodgkin's Disease (10)								
201	Hodgkin's Dis	63	57,805	49,961	3,714	28,464	41,087	63,580	243,187
	Cancers of Lymphoid and Histiocytic Tissue (15)								
202	OTR Malig Neopls of Lymphoid & Histiocytic Tiss	73	51,636	53,422	10,374	21,755	35,100	61,895	293,478
	Mult Myeloma & Immunoproliferative Neopls (24)								
203	Mult Myeloma & Immunoproliferative Neopls	38	36,602	28,956	1,159	19,352	30,950	39,960	132,605
	Lymphoid Leukemia (5)								
204	Lymphoid Leuk	32	82,208	112,246	8,811	17,300	31,219	99,770	424,952
	Myeloid Leukemia (1)								
205	Myeloid Leuk	32	155,470	162,677	5,288	23,966	113,547	204,598	533,649
	Unspecified Leukemia (3)								
208	Unspecif Leuk	10	115,071	103,577	11,393	32,589	69,790	154,868	301,398
	Specific Diabetes (38)								
2506	Diab with Neurological Manifestations	39	27,434	31,236	3,152	10,217	15,041	28,923	155,023
2507	Diab with Peripheral Circulatory Disords	31	28,571	18,479	6,314	14,964	24,178	42,569	77,804
	Hemiplegia (8)								
342	Hemiplegia & Hemiparesis	32	66,568	60,738	5,005	17,880	44,714	98,747	212,010

*Where a three- or four-digit diagnosis code is specified, all four- and five-digit codes below the listed code are included. For example, the three-digit code 195 includes ICD9 codes 195.00 through 195.99. (Number in parentheses to right of condition is the condition i.d.)

TABLE 23—*Continued*

STATISTICAL SUMMARY OF TOTAL ANNUAL HEALTH EXPENDITURES FOR HIGH-COST CONDITIONS IDENTIFIED FOR STUDY, DATA USED FOR IDENTIFYING CONDITIONS—INDIVIDUALS WITH ONE INPATIENT ADMISSION FOR THE YEAR

Inpatient ICD9 Diagnosis*	Description	No. of Cases	Total Health Expenditures						
			Mean Cost	Std Dev.	Mini-mum	25th Pcntl.	Median	75th Pcntl.	Maxi-mum
	Paraplegia (4)								
3441	Paraplegia	11	85,797	64,771	8,496	53,302	64,425	101,075	232,386
	Epilepsy (28)								
3454	PTL Epilepsy, with Impairment of Consciousness	35	33,293	25,706	3,829	13,481	31,724	48,187	123,234
	Mitral Valve Disorders (9)								
394	Diss of Mitral Valve	32	54,929	36,950	5,393	24,747	57,125	66,884	177,607
396	Diss of Mitral & Aortic Valves	20	66,576	42,488	3,299	27,845	68,399	93,915	138,904
	Aortic Valve Disorders (18)								
4241	Aortic Valve Disorders	72	42,714	25,363	3,537	16,126	45,552	60,980	99,400
	Acute Myocardial Infarction (31)								
410	AMI	1204	32,305	35,300	2,413	15,649	25,044	39,075	866,948
	Coronary Atherosclerosis of Unspecif Vessel (26)								
4140	Coronary Atherosclerosis of Unspecif Vessel	216	35,349	27,197	1,680	15,232	28,163	48,910	247,643
	Paroxysmal Ventricular Tachycardia (43)								
4271	Paroxysmal Ventricular Tachycardia	66	25,091	23,436	1,585	9,536	17,521	27,312	121,532
	Subarachnoid Hemmorhage (7)								
430	Subarachnoid Hemmor	82	70,717	73,612	3,407	25,000	42,712	100,496	323,140
	Intracranial Hemmorhage (11)								
431	Intracerebr Hemmor	47	56,344	71,040	2,833	14,708	32,274	74,986	432,812
	Embolism & Thrombosis (29)								
4440	Embolism & Thrombosis of Abdmn Aorta	16	43,749	31,704	3,589	21,177	37,658	53,024	112,842
4442	Embolism & Thrombosis of Arteries of the Extrem	71	29,033	28,914	3,183	13,022	20,850	36,959	168,616
	Aneurysm (40)								
442	OTR Aneurysm	33	26,484	15,434	2,101	18,244	23,582	32,304	75,944
441	Aortic Aneurysm	86	48,702	39,809	1,542	27,933	36,546	58,368	247,814
4423	Aneurysm of Artery of Lower Extremity	10	27,949	13,397	9,824	20,056	24,429	32,304	54,407

*Where a three- or four-digit diagnosis code is specified, all four- and five-digit codes below the listed code are included. For example, the three-digit code 195 includes ICD9 codes 195.00 through 195.99. (Number in parentheses to right of condition is the condition i.d.)

TABLE 23—*Continued*

STATISTICAL SUMMARY OF TOTAL ANNUAL HEALTH EXPENDITURES FOR HIGH-COST CONDITIONS IDENTIFIED FOR STUDY, DATA USED FOR IDENTIFYING CONDITIONS—INDIVIDUALS WITH ONE INPATIENT ADMISSION FOR THE YEAR

Inpatient ICD9 Diagnosis*	Description	No. of Cases	Total Health Expenditures						
			Mean Cost	Std Dev.	Mini-mum	25th Pcntl.	Median	75th Pcntl.	Maxi-mum
	Respiratory Failure (32)								
51881	Respir Failure	58	31,393	34,740	3,364	8,653	21,305	35,725	164,147
	Liver Disorders (30)								
5715	Cirrhosis of Liver without Mention of Alcohol	19	31,040	49,947	2,539	6,839	11,494	24,965	201,703
572	Liver Abscess & Sequelae of Chron Liver Dis	21	38,822	42,392	5,713	14,463	21,272	47,644	154,015
864	Inj to Liver	32	27,486	41,900	2,304	7,776	14,685	24,123	177,250
	Chronic Pancreatitis (37)								
5771	Chron Pancreatitis	17	28,039	31,533	3,865	8,982	13,080	27,053	94,451
	Fracture of Skull (27)								
801	FX of Base of Skull	97	33,650	116,394	1,200	3,888	6,908	18,070	814,928
	Fracture Vertebral Column With Spinal Injury (2)								
806	FX of Verteb Column w Spinal Cord Inj	15	133,941	122,110	24,370	35,621	72,133	197,776	474,416
	Chronic Renal Disease (16)								
585	Chron Renal Failure	98	48,677	45,993	2,133	18,562	34,187	70,453	278,479
586	Renal Failure, Unspecif	18	31,559	23,650	2,861	9,329	26,627	46,686	72,433
	Systemic Sclerosis (33)								
7101	Systemic Sclerosis	12	31,333	39,905	4,552	4,564	15,848	33,207	113,979
	Aseptic Necrosis of Bone (41)								
7334	Aseptic Necros of Bone	73	26,058	10,961	4,296	16,882	26,446	32,460	54,435
	Kyphoscoliosis & Scoliosis (22)								
7373	Kyphoscoliosis & Scoliosis	65	41,557	20,397	3,666	29,754	41,697	52,775	106,129
	Ventricular Septal Defect (12)								
7452	Tetralogy of Fallot	14	54,646	24,996	12,521	42,424	48,068	62,348	117,578
7454	Ventricular Septal Defect	26	63,879	124,159	5,081	28,911	41,458	48,583	664,226
	Atrial Septal Defect (21)								
7455	Ostium Secundum Type Atrial Septal Defect	38	41,592	26,593	6,993	27,668	36,813	43,545	130,039

*Where a three- or four-digit diagnosis code is specified, all four- and five-digit codes below the listed code are included. For example, the three-digit code 195 includes ICD9 codes 195.00 through 195.99. (Number in parentheses to right of condition is the condition i.d.)

TABLE 23—*Continued*
STATISTICAL SUMMARY OF TOTAL ANNUAL HEALTH EXPENDITURES FOR HIGH-COST CONDITIONS IDENTIFIED FOR STUDY, DATA USED FOR IDENTIFYING CONDITIONS—INDIVIDUALS WITH ONE INPATIENT ADMISSION FOR THE YEAR

Inpatient ICD9 Diagnosis*	Description	No. of Cases	Total Health Expenditures						
			Mean Cost	Std Dev.	Mini-mum	25th Pcntl.	Median	75th Pcntl.	Maxi-mum
	Congenital Anomalies of Spine (34)								
7561	Congen Anomal of Spine	54	29,907	17,276	3,843	18,068	24,401	34,686	78,290
	Short Gestation/Low Birthweight (39)								
765	Disords Relating to Short Gestation & Unspecif Low Birthweight	143	26,794	33,351	1,332	7,375	18,075	35,735	221,914
	Respiratory Distress in Newborn (17)								
769	Respir Distress Syndrome in Newb	48	46,362	76,029	3,191	13,662	23,169	46,237	382,880
	Complications of Devices, Cardiac Implants and Grafts (25)								
9964	Mechanical Complic of Internal Orthopedic Device, Implant, &	93	35,625	19,277	3,497	21,036	33,178	44,128	102,945
9960	Mechanical Complic of Cardiac Device, Implant, & Graft	63	39,384	30,478	3,861	17,989	28,989	54,186	115,597
9967	OTR Complics of Internal (Biological) (Synthetic) Prosthetic	91	28,233	24,620	1,755	12,223	20,011	41,075	130,428

*Where a three- or four-digit diagnosis code is specified, all four- and five-digit codes below the listed code are included. For example, the three-digit code 195 includes ICD9 codes 195.00 through 195.99. (Number in parentheses to right of condition is the condition i.d.)

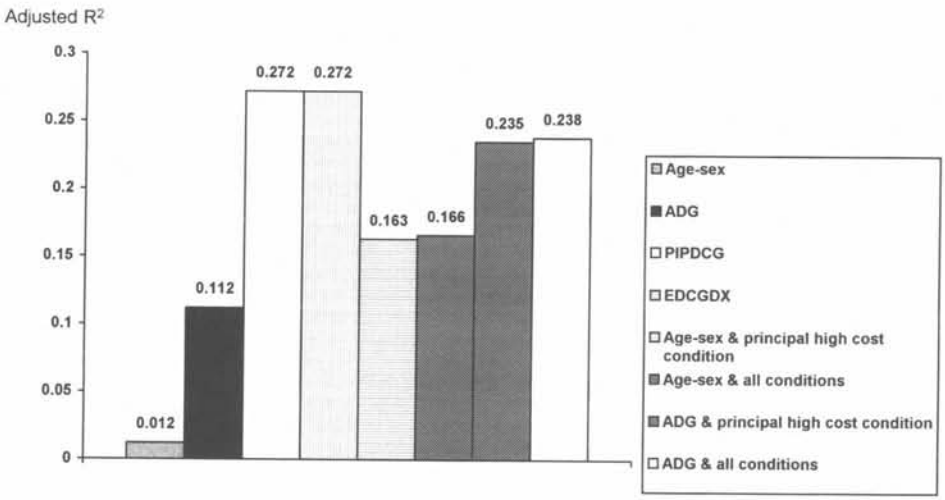
TABLE 24
FREQUENCY OF IDENTIFIED HIGH-COST CONDITIONS AND THE PERCENTAGE OF TOTAL INDIVIDUAL HEALTH CARE EXPENDITURES OVER $25,000 THEY REPRESENT AS COMPUTED FROM SAMPLE OF DATA—SEVEN POOLS—USED TO ESTIMATE PREDICTIVE ACCURACY OF HIGH-COST CONDITION AND COMPARISON MODELS (CONDITIONS SORTED BY AVERAGE ANNUAL TOTAL EXPENDITURES)

I.D.	Condition	Incidence per 100,000 Enrollees	Percentage of All Total Individual Expenditures over $25,000
1	Myeloid leukemia	1.3	0.9 %
2	Fracture vertebral column w spinal injury	0.4	0.1
3	Unspecified leukemia	1.6	1.2
4	Paraplegia	0.8	0.2
5	Lymphoid leukemia	1.9	0.7
6	Cancer of the esophagus	1.0	0.1
7	Subarachnoid hemorrhage	3.2	1.0
8	Hemiplegia	1.2	0.3
9	Mitral valve disorders	1.3	0.3
10	Hodgkin's disease	2.7	0.6
11	Intracranial hemorrhage	2.2	0.3
12	Ventricular septal defect	1.2	0.1
13	Cancers of bone, cartilage, connective, soft tissue	4.3	0.6
14	Lymphosarcoma and reticulosarcoma	1.6	0.2
15	Cancers of lymphoid and histiocytic tissue	4.5	0.9
16	Chronic renal disease	7.4	1.1
17	Respiratory distress in newborn	2.0	0.2
18	Aortic valve disorders	2.7	0.3
19	Cancers brain, resp & digest systems, except esoph	44.4	5.1
20	AIDS	1.6	0.9
21	Atrial septal defect	1.2	0.1
22	Kyphoscoliosis & scoliosis	1.3	0.0
23	Secondary cancers	13.0	2.2
24	Mult myeloma & immunoproliferative neoplasm	2.2	0.4
25	Complications of devices, cardiac implants & grafts	9.4	1.0
26	Coronary atherosclerosis of unspecif vessel	55.1	5.1
27	Fracture of skull	3.1	0.1
28	Epilepsy	1.2	0.1
29	Embolism & thrombosis	3.2	0.2
30	Liver disorders	3.0	0.4
31	Acute myocardial infarction	40.7	2.8
32	Respiratory failure	2.7	1.1
33	Systemic sclerosis	0.4	0.1
34	Congenital anomalies of spine	1.2	0.1
35	Other skin cancer	1.3	0.1
36	Cancers of other, ill-defined or unspecified sites	3.2	0.4
37	Chronic pancreatitis	0.9	0.5
38	Specific diabetes	2.4	0.2
39	Short gestation/low birthweight	4.5	0.2
40	Aneurysm	3.7	0.2
41	Aseptic necrosis of bone	2.2	0.0
42	Cancers of the reproductive systems (male & female)	54.2	2.7
43	Paroxysmal ventricular tachycardia	3.4	0.2
	Total (for above conditions)		35.2
	All other conditions for individuals with > $25,000	396.6	64.8

TABLE 25
ANALYSIS OF HIGH-COST CONDITIONS
SUMMARY OF PREDICTIVE ACCURACY—INDIVIDUAL RESULTS
RETROSPECTIVE (1992) ANALYSIS USING DATA FROM SEVEN POOLS, NO TRUNCATION OF EXPENDITURES

Risk Assessment Method	Mean Actual and Predicted	Absolute Error		Percentage Absolute Error				Adjusted R^2
		Mean	Standard Deviation	Within $500	Within $1000	Over $5000	Over $10,000	
Age-Sex	1,500	2,015	7,454	20	47	4.7	2.3	.012
ADG		1,727	7,115	46	65	6.9	2.0	.112
PIPDCG		1,482	6,464	42	69	5.1	2.4	.272
EDCGDX		1,561	6,441	44	68	5.1	2.2	.272
Age-Sex with principal high cost conditions		1,871	6,857	21	49	4.8	2.4	.163
Age-Sex with all conditions		1,870	6,844	21	49	4.8	2.4	.166
ADGs with principal high cost conditions		1,571	6,609	49	61	5.3	1.8	.235
ADGs with all conditions		1,570	6,597	49	68	5.3	1.8	.238

FIGURE 13
ANALYSIS OF HIGH-COST CONDITIONS, SUMMARY OF PREDICTIVE ACCURACY, INDIVIDUAL RESULTS, RETROSPECTIVE 1992, DATA FROM SEVEN POOLS, NO TRUNCATION—ADJUSTED R^2



with ADGs perform almost identically and come quite close to that, with adjusted R^2s of about 0.24. Age and sex alone, as expected, do very poorly, while ADGs alone reach only 0.112. Age and sex with high-cost conditions attain R^2s of 0.16 and 0.17.

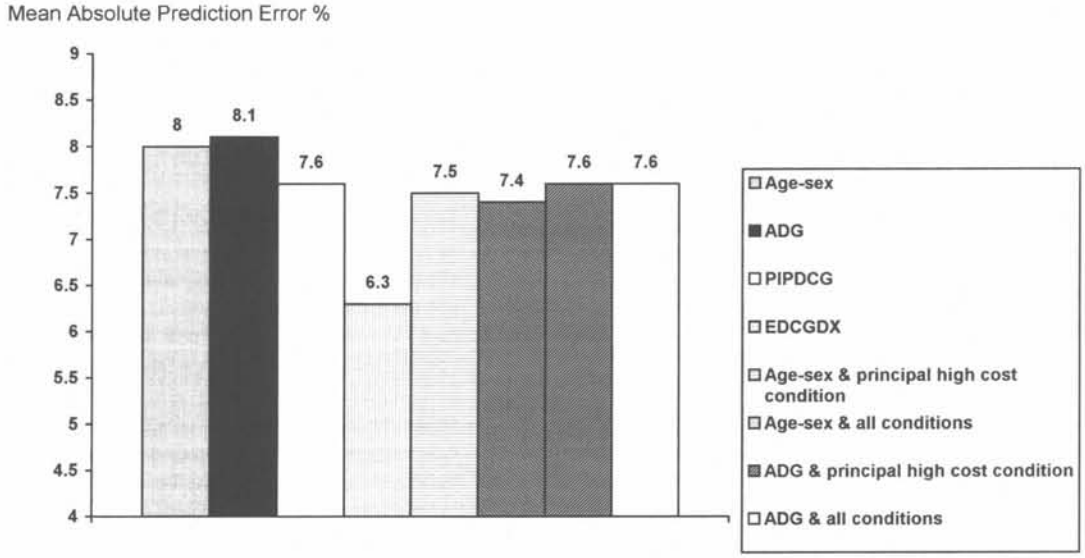
Analyses at the group level produce essentially similar results (Table 26). As Figure 14 illustrates, in terms of mean absolute prediction error, the EDCGDX model performs best. Age and sex and ADGs alone perform worst on this measure, with PIPDCGs and all the high-cost-condition models performing similarly and noticeably less well than EDCGDXs. On the other measures PIPDCGs perform almost as well as EDCGDXs, and better than the high-cost-condition models. Age and sex and ADGs alone always perform worst, though their relative ranking depends on the specific measure used.

Finally, for exploratory purposes, we combined our high-cost conditions with the PIPDCG model. We did this to investigate whether any of the predictive power of the conditions would supplement that from PIPDCGs. This combined model produced an adjusted

TABLE 26
ANALYSIS OF HIGH-COST CONDITIONS
SUMMARY OF PREDICTIVE ACCURACY—GROUP RESULTS
RETROSPECTIVE (1992) ANALYSIS USING DATA FROM SEVEN POOLS, NO TRUNCATION OF EXPENDITURES

Risk Assessment Method	Mean		Standard Deviation		% Absolute Error	
	Absolute Error	Absolute % Error	Absolute Error	Predictive Ratio	Within 5%	Within 10%
Age-Sex	120	8.0	102	0.99	39	69
ADG	120	8.1	106	0.98	43	68
PIPDCG	114	7.6	97	0.99	40	77
EDCGDX	95	6.3	77	1.01	44	81
Age-Sex with principal high cost conditions	112	7.5	101	0.99	43	72
Age-Sex with all conditions	111	7.4	100	0.99	44	74
ADGs with principal high cost conditions	113	7.6	102	0.98	47	73
ADGs with all conditions	113	7.6	100	0.99	48	76

FIGURE 14
ANALYSIS OF HIGH-COST CONDITIONS, SUMMARY OF PREDICTIVE ACCURACY, RANDOM GROUP RESULTS, RETROSPECTIVE 1992, DATA FROM SEVEN POOLS, NO TRUNCATION—MEAN ABSOLUTE PREDICTION ERROR



R^2 of 0.321 compared with a value of 0.272 for PIPDCGs alone. Also, interestingly, with the exception of a single high-cost condition, the estimated risk weights for all conditions we developed were positive, suggesting that we had identified diagnoses of higher expected costs within each PIPDCG. These findings suggest the retrospective PIPDCG model might be improved with the addition of some of the information provided by our high-cost list.

E. Discussion

We found that, although they were not specifically developed as substitutes for high-cost-condition lists,

the EDCGDX and PIPDCG models perform better, in terms of predictive accuracy, than the high-cost-condition list that we developed. The performance of the PIPDCG model is particularly striking in view of the fact that it is simpler than the EDCGDX model and relies only on inpatient diagnoses. Since the PIPDCG (and EDCGDX) model we tested also includes age and sex, it can be compared directly with the age and sex with and without our list of high-cost conditions. As shown, the PIPDCG model does substantially better than age and sex with high-cost conditions, which are also based only on inpatient diagnoses.[7]

Taking into account the occurrence of multiple primary inpatient diagnoses improved the predictive accuracy of the high-cost list only slightly, in good part because, as described above, only 5% of the individuals with one or more high-cost conditions had two or more, and only 0.3% had three. Allowing for interactions between high-cost conditions would probably then yield an even smaller payoff.

The list of diagnosis groups on which our results are based has the advantage of having been derived from a large, national data set. An extensive process of clinical evaluation, comparable to that used in development of the HIPC list, was beyond the scope of our project.

We included in our list only ICD9 diagnoses, and no procedures. In doing so, we followed the pattern set by the HIPC. This allows the method to be used prospectively as well as retrospectively. If retrospective payment is to be used, high-cost procedures such as transplants could be added to the list. Again, however, the addition of only a limited list of very high-cost nondiscretionary procedures (such as transplants, as in the current New York list) would probably contribute fairly little to the model.

The PIPDCG model is not fundamentally different from a list of high-cost conditions, except that it includes some lower cost conditions as well.[8] In spite of the fact that it aggregates many high-cost conditions more than our list does, it outperforms it even when our list is combined with ADGs. This suggests that those wishing to develop a list of high-cost conditions may also benefit from a careful study of the construction of the DCG models.[9] Combining this with analysis of a large data set such as ours, and an extensive clinical review such as the HIPC used, should yield a better list of high-cost conditions than any currently available.

END NOTES

1. In addition to being relatively small in number, we did not observe any common ambulatory diagnoses for high-cost individuals without an inpatient admission.
2. ICD9 codes can be recorded using three, four, or five digits. The first three digits indicate a family of clinical conditions. For example, ICD9 code 320 represents bacterial meningitis. Meningitis due to other specified bacteria (as opposed to, for example, pneumococcal meningitis, which is coded as 320.1) is coded as 320.8. A more specific diagnosis of anaerobic meningitis is coded as 320.81. Many four-digit codes have no five-digit subdivisions, which may explain in part why a number of carriers only record four digits.
3. The reason we did this was to make the assignment of costs to diagnoses unambiguous. As indicated in the text, we accomplished this by summarizing expenditures at the three-, four-, and five-digit level for individuals who had only one principal inpatient diagnosis. (Such individuals could have had more than one admission as long as all admissions were coded with the same principal inpatient diagnosis.) This does not mean that we excluded individuals with multiple conditions from these high-cost analyses. We excluded them only for this step. Individuals with multiple admissions *and* multiple principal inpatient diagnoses were included in subsequent analyses, as described below.
4. Where a three- or four-digit diagnosis code is specified, all four- and five-digit codes below the listed code are included. For example, the three-digit code 195 includes ICD9 codes 195.00 through 195.99.
5. No individual in the data set had more than three different high-cost diagnoses.
6. To increase the number of observations for the high-cost cases in the sample, we did not use a split-half approach. Other exploratory analyses indicated that our findings are not sensitive to this decision.
7. One fundamental difference between the PIPDCG and EDCGDX models and our list of high-cost conditions is that, while our list is restricted to conditions with average expenditures greater than $25,000, the DCG models consider diagnoses with expenditures under that amount. As a result, these models might be expected to perform better for "medium cost" diagnoses.
8. The same is not true of the EDCGDX model, which makes use of ambulatory diagnoses, and combines the information in a more complex way than either the PIPDCG model or a list of high-cost conditions.
9. In addition to the PIPDCG model, the EDCGDX model, for example, takes comorbidities into account in a manner that might be incorporated into a list of high-cost conditions.