Measuring Population Health Risks Using Inpatient Diagnoses and Outpatient Pharmacy Data

Yang Zhao, Randall P. Ellis, Arlene S. Ash, David Calabrese, John Z. Ayanian, James P. Slaughter, Lori Weyuker, and Bruce Bowen

Objective. To examine and evaluate models that use inpatient encounter data and outpatient pharmacy claims data to predict future health care expenditures.

Data Source / Study Design. The study group was the privately insured under-65 population in the 1997 and 1998 MEDSTAT MarketScan® Research Database. Pharmacy and disease profiles, created from pharmacy claims and inpatient encounter data, respectively, were used separately and in combination to predict each individual's subsequent-year health care expenditures.

Principal Findings. The inpatient-diagnosis model predicts well for the low-hospitalization under-65 populations, explaining 8.4 percent of future individual total cost variation. The pharmacy-based and inpatient-diagnosis models perform comparably overall, with pharmacy data better able to split off a group of truly low-cost people and inpatient diagnoses better able to find a small group with extremely high future costs. The model that uses both kinds of data performed significantly better than either model alone, with an R^2 value of 11.8 percent.

Conclusions. Comprehensive pharmacy and inpatient diagnosis classification systems are each helpful for discriminating among people according to their expected costs. Properly organized and in combination these data are promising predictors of future costs.

Key Words. Diagnostic cost group (DCG), pharmacy profile, population health management, predictive models, risk assessment

Each population not only has unique demographic and socioeconomic characteristics but also a distinct medical signature. After nearly two decades of development, risk models that combine diagnoses from patient-clinician encounters across the spectrum of health care delivery sites with age and sex are now being used by health care organizations to measure the health risk of populations. However, many organizations have not implemented "all-encounter" diagnosis models because they require timely, comprehensive, high-quality data from physician's offices and other dispersed sites of care.

Models to predict next year's cost for individuals have been developed on a range of prior-year information. The earliest diagnosis-based models were developed on Medicare data and relied exclusively on principal diagnoses from hospitalizations (Ash, Porell, Gruenberg, et al. 1989; Newhouse et al. 1989; Pope, Ellis, Ash, et al. 2000). Inpatient models predict next year's total costs reasonably well in Medicare, where nearly 20 percent of the population is hospitalized annually, often for chronic conditions. However, such models are less attractive for privately insured under-65 populations, where fewer than 5 percent are hospitalized in a year and often for acute conditions. Few previous studies have evaluated inpatient diagnosis models on younger populations. So-called all-encounter models that use both inpatient and outpatient diagnoses to predict cost have been developed for several types of populations: elderly (Ellis and Ash 1995; Ellis, Pope, Iezzoni, et al. 1996; Weiner, Dobson, Maxwell, et al. 1996), disabled (Ash, Ellis, Pope, et al. 2000; Kronick et al. 1996; Kronick et al. 2000; Weiner, Tucker, Collins, et al. 1998), and employer groups (Ash, Ellis, Pope, et al. 2000; Starfield et al. 1991; Weiner et al. 1991). These models are more powerful than those limited to inpatient data; however, the data they require are not always available. Several studies have predicted future health care costs from widely available pharmacy claims (Clark, Von Korff, Saunders, et al. 1995; Fishman and Shay 1999; Johnson, Hornbrook, and Nichols 1994; Lamers 1999; Malone et al. 1999; Roblin 1998), but none have combined pharmacy claims and inpatient diagnoses.

Used for hospital reimbursement and case management, inpatient encounter claims are now widely available and are generally of high quality and routinely subject to screening and validation. Although risk models that use both inpatient and outpatient diagnoses to predict cost have much better predictive power than those limited to inpatient data only, many health care organizations do not have complete or consistent data on diagnoses from outpatient encounters. On the

---

Address correspondence to Yang Zhao, Ph.D., Senior Research Associate, D_xCG, Inc., 25 Kingston Street, Suite 200, Boston, MA 02111. Randall P. Ellis, Ph.D., is Professor, Department of Economics, Boston University, and Senior Scientist, D_xCG, Inc. Arlene S. Ash, Ph.D., is Research Professor, Department of General Internal Medicine, Boston University, and Senior Scientist, D_xCG, Inc. David Calabrese, R.Ph., M.H.P., is Director of Pharmacy, CareGroup Provider Service Network, Boston. John Z. Ayanian, M.D., M.P.P., is with the Division of General Medicine, Brigham and Women's Hospital, and Department of Health Care Policy, Harvard Medical School, and is a Consultant with D_xCG, Inc. James P. Slaughter, M.D., is Chair, Medical Records Group, Kaiser Permanente, San Rafael, CA. Lori Weyuker, A.S.A., is an Actuary, Kaiser Permanente, Oakland, CA. Bruce Bowen, Ph.D., is an Executive Consultant, Kaiser Permanente. This article, submitted to *Health Services Research* on July 30, 2001, was revised and accepted for publication on October 18, 2001.

other hand, timely and high-quality electronic outpatient pharmacy data are widely available. Combining inpatient and pharmacy data to predict future health care spending is attractive in situations where all-encounter claims data of sufficient quality are not available.

This article develops and evaluates models that use pharmacy and inpatient information to predict subsequent-year health care spending. We first describe a new system for constructing person-specific pharmacy-based profiles and predicting costs from these profiles. We also develop a diagnosis-based model using only inpatient information and explore how pharmacy and inpatient information can be combined to predict health risk. For comparison we develop an all-encounter, diagnosis-based model using both inpatient and outpatient information. Finally, we evaluate each model's predictive performance on a large, commercially insured, under-65 population.

METHODS

Data

We developed our models on a population of 1,000,000 nationally disbursed individuals eligible for health care coverage through large employers in 1997 and 1998. Included individuals had at least one month of enrollment in each year and pharmacy coverage whenever enrolled. About two-thirds (66 percent) were in fee-for-service plans; all were under age 65.

Our outcome was total covered expenditures in 1998, including both deductibles and copayments, and was aggregated from inpatient admission, outpatient service, and outpatient drug claims. Typical of many privately insured populations, 15 percent were not enrolled for all of 1998. For each partial-year enrollee we calculated the fraction of the year eligible and an annualized expenditure (actual spending divided by the eligibility fraction); in modeling we used annualized expenses as the outcome and eligibility fractions as weights.

RxGroups and Rx Profiles

Previous studies selected drugs that are commonly used for the treatment of specific chronic conditions and grouped them into approximately 30 diagnostic categories such as diabetes mellitus, hypertension, and asthma. Because few drugs are highly indicative of specific medical problems only a handful of drugs were recognized. Our approach was to develop a comprehensive Rx classification system that

would identify all the prescription (Rx) drugs each individual filled over a fixed period. The main criterion used to classify each drug was therapeutic indication. We classified each of more than 58,000 National Drug Codes into one of 127 mutually exclusive categories (called RxGroups). For structural clarity these groups were further clustered into 18 aggregated Rx categories (ARC) encompassing broad categories of drugs, based upon their most common uses. ARCs typically identify the major organ system with which an agent interacts (e.g., cardiovascular drugs) or the agent's primary pharmacologic activity (e.g., anti-infectives). Both ARCs and RxGroups can be used to create Rx profiles for individuals and populations. However, only RxGroups are used to predict future costs.

Rx Model Construction

A model to predict costs from pharmacy data should predict accurately, be robust to common variations in prescribing, and be understandable and credible to clinicians. We used hierarchies, pooling, and "dropping" of RxGroups to achieve these goals. Hierarchies impose "dominance" relationships among RxGroups that are used to treat the same medical problem. For example, a person with diabetes might take insulin or oral hypoglycemic agents alone or in combination. Typically, those taking insulin have more severe or refractory disease than those taking only oral hypoglycemic agents. However, a person who uses both oral drugs and insulin during a year is not necessarily sicker than one who uses insulin alone. Thus, we placed the RxGroup for insulin above the RxGroup for oral diabetic agents in a "diabetes drugs" hierarchy so that only people who were not using insulin were credited (in the model) with using oral diabetic agents. This ensured that the model coefficient for oral diabetic agents was based only on the costs incurred by less severely ill people.

We pooled RxGroups in our model when they were used almost interchangeably for the same kinds of medical problems. For example, new antiretroviral drugs for treating HIV infection and AIDS may have different functions and higher costs than older drugs, although the use of either kind of drug generally indicates a patient with HIV infection (except for brief prophylactic uses). When RxGroups are pooled, the model treats combinations of these drugs the same as if any one was the sole agent prescribed.

We dropped a few RxGroups from the model, which means that we set their model coefficients to zero. Dropped RxGroups fell primarily into three categories: drugs, such as oral corticosteroids, widely used for a range of unrelated medical problems; drugs, such as antacids, that are available in both over-

the-counter and prescription forms, making data capture unreliable; and drugs, such as diagnostic testing supplies, that are used primarily to confirm or rule out a medical condition. Additional RxGroups, such as oral contraceptives, were dropped because they did not predict future costs. To avoid people being seen as less sick because they filled a particular prescription, we also zeroed out the coefficients of RxGroups, such as peripheral vasodilators, with negative coefficients. Most of the negative values were small and not statistically significant, and our clinicians did not believe that any of them captured important relationships between likely disease status and future costs.

RxGroup Interactions

People with multiple medical problems often take many drugs, and particular combinations of drugs may suggest differential disease severity than the individual drugs alone. We explored adding markers for combinations of drug groups to empirically identify such interactions. Positive interactions indicate that the combined effect is larger than the sum of individual effects; negative interactions indicate smaller combined effects.

We selected from an exhaustive set of both two- and three-way RxGroup interactions according to four criteria. Most importantly, the combinations had to have clinical face validity, that is, clinicians had to believe that the disease severity inferred from the combined drugs was substantially different than indicated by the drugs individually. Second, to be considered, an RxGroup combination could not be too rare (it must occur for at least 500 people of the 1,000,000 in our database). Third, we enforced monotonicity; we did not introduce interactions that resulted in a lower prediction for a pair of drugs than would occur if only one of the drugs were present. Fourth, all interaction terms had to be statistically significant at the .05 level.

DCG Inpatient/All-encounter Diagnosis Modeling

Using the same structure used to build the all-encounter Diagnostic Cost Group (DCG) model (Ash, Ellis, Pope, et al. 2000), we first mapped both diagnoses coded during inpatient admissions and diagnoses coded during outpatient patient-clinician encounters into one of 118 clinically homogenous condition categories (CC). Hierarchies were imposed on the CCs to generate hierarchic condition categories (HCC), which identify the most costly manifestation of each distinct medical problem. Although the number of times a diagnosis appears

does not affect the CC assignment, individuals with several distinct diagnoses are recognized in several HCCs. A person's HCCs form a disease-burden profile that identifies his or her medical problems in year one; this profile is used to predict year-two expenditures.

Model Development

We used linear regression to estimate year-two costs. All models contained markers for age and sex. The inpatient-only model (IPHCC) also used HCCs, generated from inpatient diagnoses only, as predictors. We used HCCs generated from both inpatient and outpatient diagnoses in the all-encounter model (HCC). For the RxGroup model, we used RxGroups and selected RxGroup interactions. Finally, for the Rx + inpatient diagnoses model (Rx + IPHCC) we used RxGroups, selected RxGroup interactions, and inpatient HCCs.

Evaluation

We used the same development population to evaluate each model's predictive accuracy. In addition to the traditional R^2, which measures the percentage of individual total cost variation explained by a model, we examined the ability of each model to identify people with extreme costs. For each model, we classified all individuals into deciles of model-predicted risk and compared the mean actual costs of people in various deciles according to the different models. More discriminating models yield more extreme distinctions across the deciles than less powerful models; their first and second decile groups incur lower costs, and their ninth and tenth deciles incur higher costs. We also computed for each model the ratio of actual year-two costs in decile ten versus decile one.

An important criterion for evaluating a model is how well its predictions match actual expenditures for key population subgroups (Ash and Byrne-Logan 1998) such as those formed by percentiles of increasing year-one cost. However, there is no natural order for assigning the approximately 22 percent of people with zero year-one expenses to percentiles one through 22. Although a second sort variable (such as ascending age) could be used to "break the ties," we instead used a random variable to assign the zero-cost cases to percentiles. We next computed the mean actual year-two costs and the mean costs predicted by each of the four models within each percentile group and plotted each of the 100 model-predicted averages (on the x axis) against the actual average for the same percentile group (on the y axis). The 45-degree line was also plotted; the shorter the

horizontal distance from a point to the 45-degree line, the closer the predicted and actual costs for that group and model.

RESULTS

Table 1 summarizes population demographics and utilization experience. In year one more than one-third of people (35.6 percent) were neither hospitalized nor received drugs through the pharmacy data, and only 4.3 percent of people were hospitalized. Average year-two costs varied from a low of $723 for the no-hospital/no-drug group to $7,822 for the group with both kinds of utilization.

Table 2 shows how the prevalence of the 18 ARCs as rates per 10,000 people varied by sex or age. Notice that women were more likely to take endocrine/metabolic, genitourinary, and nutritional drugs, whereas men were more likely to have antihyperlipidemic or biologic (including anticoagulant) drugs. The pattern of drug use also varied by age. Drug use for chronic medical conditions, such as cardiovascular disease and diabetes, was more prevalent among adults, whereas more children (that is, those under age 18) used drugs for eye, ear, nose, and throat problems.

In Table 3, we show the prevalence and model coefficients associated with the RxGroups that comprise three important ARCs: the very common anti-infectives (prescribed at least once during year one to more than 40 percent of people), the common and important cardiovascular drugs (used by 11 percent of

Table 1: Demographics and Utilization Experience in a Privately Insured Population (N = 1,083,405)

	% of People	*Year-two Mean Costs ($)*	*Year-two Costs ($) (Standard Deviation)*
All	100.0	1,901	8,515
Female	50.2	2,143	8,003
Male	49.8	1,657	8,995
Age (y.) (mean 32.8)			
0–17	26.2	773	4,938
18–44	41.5	1,546	6,236
45–64	32.3	3,265	12,325
Year-one utilization status			
Neither Rx nor inpatient claims	35.6	723	4,275
Only Rx claims	60.1	2,204	6,754
Only inpatient claims	0.5	4,095	41,965
Both Rx and inpatient claims	3.8	7,822	27,434

Table 2: Prevalence Rates per 10,000 of Aggregated Rx Categories (ARC) by Sex or Age

ARC	*Label*	*All*	*Male*	*Female*	*Adults**	*Children**
1	Analgesics / anti-inflammatories	2,248	1,936	2,557	2,808	686
2	Antihyperlipidemics	372	443	301	503	4
3	Anti-infectives	4,343	3,858	4,824	4,275	4,534
4	Biologicals	77	91	63	102	5
5	Cardiovascular	1,110	1,062	1,156	1,476	89
6	Central nervous system agents	1,218	905	1,528	1,461	542
7	Dermatologicals	987	829	1,143	1,036	849
8	Diabetes drugs	195	219	171	259	17
9	Eye, ear, nose, throat preps	771	701	841	654	1,097
10	Endocrine / metabolic agents	1,718	687	2,739	2,134	557
11	Genitourinary agents	446	208	582	567	109
12	Gastrointestinal drugs	960	781	1,137	1,180	348
13	Immunologic agents	38	27	49	50	4
14	Neuromuscular agents	486	411	560	628	90
15	Nutritionals	457	255	657	481	390
16	Pulmonary drugs	595	561	629	496	872
17	Upper respiratory agents	2,374	2,048	2,697	2,518	1,975
18	Additional groups	984	825	1,141	1,076	729

*Adults are aged 18 to 64; children are aged up to 17.

Table 3: Prevalence Rates per 10,000 and Increment to Year-two Cost Prediction for the Selected Drugs

RxGroup/Label	*Prevalence*	*Increment, RxGroup**	*Increment, Rx + IPHCC**
Anti-infectives	4,313	—	—
7 Amebicides	4	0	0
8 Anthelmintics	20	0	0
9 Antiherpetics	159	409	316
10 Anti-infectives	4,215	184	159
11 Antimalarials	26	1,016	701
12 Antineoplastics	30	3,065	2,497
13 Azole antifungals	212	566	400
14 Influenza drugs	39	0	0
15 Leprostatics	1	3,950	2,275
16† Non-nucleoside reverse transcriptase inhibitors 17† Nucleoside reverse transcriptase inhibitors 18† Protease inhibitors 19† Miscellaneous antivirals	6	9,341	8,256

Continued

RxGroup/Label	Prevalence	Increment, RxGroup*	Increment, Rx + IPHCC*
Cardiovascular	1,100	—	—
32 Agents for hypertensive emergencies	0	0	0
33 Angiotensin converting enzyme inhibitor	316	567	502
34 Angiotensin II inhibitors	41	1,001	892
35 Antiadrenergic agents, centrally acting	37	1,326	875
36 Antiadrenergic agents, peripherally acting	87	1,090	957
37 Antianginal agents	76	2,010	1,742
38 Antiarrhythmic agents	12	2,112	2,092
39 Antihypertensive combinations	266	64	192
40 Beta-adrenergic blocking agents	304	534	477
41 Calcium channel blocking agents	328	1,219	1,093
42 Inotropic agents	38	826	464
43 Loop diuretics	90	2,038	1,447
44 Peripheral vasodilators	2	0	0
45 Potassium-sparing diuretics	19	3,337	2,359
46 Pulmonary hypertension drugs	0	0	0
47 Thiazide diuretics	177	0	0
48 Vasodilators	4	1,483	0
49 Vasopressors	30	286	301
50 Miscellaneous cardiovascular agents	1	1,316	0
Diabetes Drugs	195	—	—
66 Insulin	70	2,332	2,130
67 Oral diabetic agents (but not insulin)	125	1,462	1,321

*Dollar increment to year-two cost prediction in the RxGroup and Rx + IPHCC models associated with a year-one drug in this RxGroup.
‡RxGroups are pooled in the model such that any combination of drugs from these RxGroups is treated the same as if only one were prescribed.

people), and the less common but still important diabetes medicines (used by 2 percent). A listing of all the coefficients and *t*-statistics for the Rx-based models is available from the authors. Note that some RxGroups had zero prevalence in our sample, whereas some RxGroups were dropped from the model. Dropped RxGroups had nonzero prevalence but zero coefficients. In addition to the 127 RxGroups 23, two- and three-way RxGroup interactions were included in both the RxGroup and Rx + IPHCC models. All the interaction terms had positive coefficients, indicating that the combined effects were bigger than the sum of individual effects. Only a few interactions that were not statistically significant were present; they were included because clinicians believe that they make clinical sense. The Rx + IPHCC model also included 118 HCCs generated from inpatient diagnoses.

Table 4 shows that the IPHCC and RxGroup models each had R^2 values approximately equal to 8.4 percent. Combining Rx and inpatient diagnoses signifi-

cantly improved predictive power, increasing the R^2 to 11.8 percent, which is very similar to the R^2 of the all-encounter model (11.3 percent). Both Rx-based models were better at identifying people with extreme costs than the IPHCC model. Among the highest risk decile groups identified by each of the four models, people identified by IPHCC (a model that only "sees" risk when people are hospitalized) were only about 75 percent as expensive as those identified by either of the models that incorporate pharmacy data. Similarly, costs for people in the lowest decile identified by the IPHCC were 40 percent higher than costs for those in the lowest decile of either pharmacy-reliant model. The all-encounter HCC model was somewhat better than the Rx-based models at identifying the lowest risk people, producing the greatest overall spread.

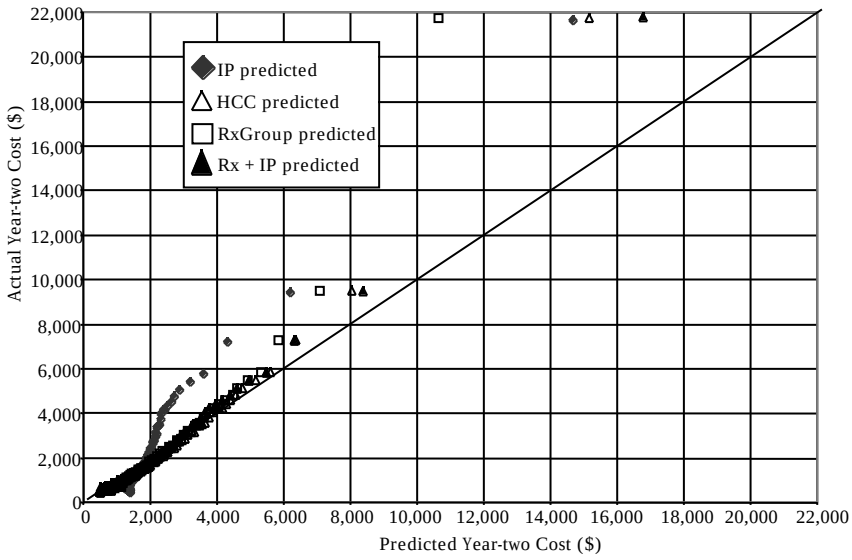
Figure 1 compares predicted to actual year-two costs within percentile groups of actual year-one costs. The HCC and Rx-based model predictions were closer to actual costs than the IPHCC predictions for all percentile groups except the top one. Overall the two Rx-based model predictions were very similar to the HCC predictions except for groups that cost more than $5,000, where the RxGroup predictions substantially underestimated the actual costs. Among people in the top three percentile groups, Rx + IPHCC predictions were closest to the 45-degree line, where predictions equal actual costs. All four models underpredicted the most expensive group, which averaged $21,661 in year two. The RxGroup model predicted costs of $10,533, only half of actual costs. The IPHCC model performed better, predicting $14,672, or 68 percent of actual costs. The HCC model prediction was $15,080, or 70 percent of actual costs. The Rx + IPHCC model predicted best at $16,659, or 79 percent of actual costs.

Table 4: Performance of Models to Predict Costs:
Mean Year-two Costs by Decile of Model-predicted Risk

Model	R^2 *(%)*	*Decile One ($)*	*Decile Two ($)*	*Decile Nine ($)*	*Decile Ten ($)*	*Ratio**
IPHCC	8.44	52	641	3,032	5,449	10.2
HCC	11.30	292	444	3,297	7,488	25.6
RxGroup	8.35	385	560	3,194	7,185	18.7
Rx + IPHCC	11.75	363	519	3,159	7,453	20.5

*Ratio = (decile ten mean year-two costs) / (decile one mean year-two costs).

Figure 1: Year-two Predicted Versus Actual Costs for Percentile Groups Based on Year-one Cost



DISCUSSION

We have compared the predictive power of four risk-adjustment models that use various combinations of diagnoses, pharmacy data, or both to predict future health expenditures. Using only partial information to measure population health status, IPHCC and RxGroup models predict total costs reasonably well, with the RxGroup model predicting better for low-cost healthy people and the IPHCC model better identifying the very highest cost people. Combining pharmacy and inpatient claims improved model performance significantly and provided a more complete picture of the distribution of illness in the population. The gain is principally due to being able to identify both the healthiest people (with both no or only "time-limited" pharmacy use and no hospitalizations) and the sickest (who are hospitalized for chronic illness). Overall the predictive performance of the Rx + IPHCC model compared well with that of the gold standard all-encounter (HCC) model.

Inpatient diagnosis codes have limited ability to describe disease burden in under-65 populations because only about 4 percent of enrollees are hospitalized.

Furthermore, many of the medical problems in these populations are acute and have few implications for future costs. Among the 96 percent of the population with no hospitalization, an inpatient model can only differentiate them by age and sex; it cannot distinguish the fully healthy from nonhospitalized people with continuing serious medical problems. However, it is surprising to see that our inpatient-only model that used all diagnoses from hospitalizations, including both principal and secondary inpatient diagnoses, had an R^2 value of 8.4 percent given the rarity of hospitalization in such populations. In contrast, the Principal Inpatient Diagnostic Cost Group (PIPDCG) model developed for Medicare (Pope, Ellis, Ash, et al. 2000) obtains an R^2 value of 6.3 percent using age, sex, and only a dominant principal inpatient diagnosis to classify individuals into one of 16 mutually exclusive categories. Although Medicare enrollees are more likely to be hospitalized for chronic diseases that are highly predictive of future health care needs, the single-condition PIPDCG model ignores the information captured by additional inpatient diagnoses, which are important for identifying comorbid medical conditions and individuals at high risk.

While hospitalization rates were low, more than 60 percent had at least one prescription drug in the base year. Unlike previous studies that identify only selected drugs that map to specific medical problems (such as insulin to diabetes, oral sulfonamides to inflammatory bowel disease), our comprehensive pharmacy classification system recognizes the complete range of prescription drugs each individual takes during the year and summarizes this information in a drug profile that is useful for clinicians and health care managers as well as for prediction.

Drug use, however, does not usually map to medical conditions; insulin for diabetes and beta interferon for multiple sclerosis are among the rare exceptions to this rule. The vast majority of drugs are used for conditions with widely different cost implications. For example, lamivudine, previously used exclusively for persons infected with HIV, is now used in managing hepatitis C. Even the presence of a disease-specific drug, such as an inhaled steroid for asthma, is not able to identify the severity of the disease. Consequently, people in Rx categories are more clinically heterogeneous than those classified using diagnosis codes, making it difficult for Rx-only models to distinguish those at highest risk.

For health plans that lack reliable all-encounter claims data, a risk model that uses both pharmacy and inpatient diagnoses may be best. Rx data can distinguish the healthiest people from those with at least one prescribed medication and also capture a sense of the range of medical problems experienced; inpatient diagnoses identify sickness among those hospitalized and can distinguish between chronic and acute problems. Comprehensive Rx and diagnostic classification

systems complement each other. Models that combine both can not only create comprehensive pharmacy and disease profiles at the individual and group levels but also identify individuals and populations that are at risk for specific diseases. These models are valuable tools for physicians, health care managers, and health plans engaged in population-based health management.

ACKNOWLEDGMENTS

We are grateful to Marilyn Schlein Kramer for her active role in helping with the development of the RxGroup models and review of this article. RxGroups™ is a trademark of $D_xCG^{®}$, Inc.

REFERENCES

Ash, A., and S. Byrne-Logan. 1998. "How Well Do Models Work? Predicting Health Care Costs." Dallas: *Proceedings of the Section on Statistics in Epidemiology of the American Statistical Association*, pp. 42–49.

Ash, A., R. P. Ellis, G. C. Pope, J. Z. Ayanian, D. W. Bates, H. Burstin, L. I. Iezzoni, E. McKay, and W. Yu. 2000. "Using Diagnoses to Describe Populations and Predict Costs." *Health Care Financing Review* 21 (3): 7–28.

Ash, A., F. Porell, L. Gruenberg, E. Sawitz, and A. Beiser. 1989. "Adjusting Medicare Capitation Payments Using Prior Hospitalization." *Health Care Financing Review* 10 (4): 17–29.

Clark, D. O., M. Von Korff, K. Saunders, W. M. Baluch, and G. E. Simon. 1995. "A Chronic Disease Score with Empirically Derived Weights." *Medical Care* 33 (8): 783–95.

Ellis, R. P., A. Ash. 1995. "Refinements to the Diagnostic Cost Group Model." *Inquiry* 32 (4): 1–12.

Ellis, R. P., G. C. Pope, L. I. Iezzoni, J. Z. Ayanian, D. W. Bates, H. Burstin, and A. Ash. 1996. "Diagnosis-based Risk Adjustment for Medicare Capitation Payments." *Health Care Financing Review* 17 (3): 101–28.

Fishman, P. A., and D. K. Shay. 1999. "Development and Estimation of a Pediatric Chronic Disease Score Using Automated Pharmacy Data." *Medical Care* 37 (9): 874–83.

Johnson, R. E., M. C. Hornbrook, and G. A. Nichols. 1994. "Replicating the Chronic Disease Score (CDS) from Automated Pharmacy Data." *Journal of Clinical Epidemiology* 47 (10): 1191–99.

Kronick, R., T. Dreyfus, L. Lee, and Z. Zhou. 1996. "Diagnostic Risk Adjustment for Medicaid: The Disability Payment System." *Health Care Financing Review* 17 (3): 7–33.

Kronick, R., T. Gilmer, T. Dreyfus, and L. Lee. 2000. "Improving Health-based Payment for Medicaid Beneficiaries: CDPS." *Health Care Financing Review* 21 (3): 29–64.

Lamers, L. M. 1999. "Pharmacy Costs Groups: A Risk-adjuster for Capitation Payment Based on the Use of Prescribed Drugs." *Medical Care* 37 (8): 824–30.

Malone, D. C., S. J. Billups, R. J. Valuck, and B. L. Carter. 1999. "Development of a Chronic Disease Indicator Score Using a Veterans Affairs Medical Center Medication Database." *Journal of Clinical Epidemiology* 52 (6): 551–57.

Newhouse, J. P., W. G. Manning, E. B. Keeler, and E. M. Sloss. 1989. "Adjusting Capitation Rates Using Objective Health Measurers and Prior Utilization." *Health Care Financing Review* 10 (3): 41–54.

Pope, G. C., R. P. Ellis, A. Ash, C. F. Liu, J. Z. Ayanian, D. W. Bates, H. Burstin, L. I. Iezzoni, and M. J. Ingber. 2000. "Principal Inpatient Diagnostic Cost Group Model for Medicare Risk Adjustment." *Health Care Financing Review* 21 (3): 93–118.

Roblin, D. W. 1998. "Physician Profiling Using Outpatient Pharmacy Data as a Source for Case Mix Measurement and Risk Adjustment." *Journal of Ambulatory Care Management* 21 (4): 68–84.

Starfield, B., J. P. Weiner, L. Mumford, and D. Steinwachs. 1991. "Ambulatory Care Groups: A Categorization of Diagnoses for Research and Management." *Health Services Research* 26 (1): 53–74.

Weiner, J. P., A. Dobson, S. Maxwell, K. Coleman, B. Starfield, and G. Anderson. 1996. "Risk-adjusted Medicare Capitation Rates Using Ambulatory and Inpatient Diagnoses." *Health Care Financing Review* 17 (3): 77–99.

Weiner, J. P, B. H. Starfield, D. M. Steinwachs, and L. M. Mumford. 1991. "Development and Application of a Population-oriented Measure of Ambulatory Case-mix." *Medical Care* 29 (5): 452–72.

Weiner, J. P, A. Tucker, M. A. Collins, H. Fakhraei, R. Lieberman, C. Abrams, G. R. Trapnell, and J. G. Folkemer. 1998. "The Development of a Risk-adjusted Capitation Payment System: The Maryland Medicaid Model." *Journal of Ambulatory Care Management* 21 (4): 29–52.