Predictive Ratios forAge and Sex

CRGs are a clinical model which only makes limited use of age and sex. If age and sex factors were to be incorporated into the estimate of future expenditures as would be the case in most applications of CRGs, the predictive ratios for age and sex categories would always equal 1.00 for any budget neutral analysis.

When predictive ratios are applied to age and sex categories, the results are as expected (See Tables 12 and 13). The healthy, in this case the young, tend to have predictive ratios above one. The older segments of the population, i.e., the sicker, have predictive ratios less than one. The one exception to this is women in child bearing years who, though not sick, incur significant pregnancy related expenditures.

The data sources also perform consistently, although with some exceptions. Previous analysis showed that the best performance was for all data sources and the worst performance was for inpatient data only. However, the predictive ratio for males under five years old was 1.223 for outpatient and drug data and 1.229 for all three data sources. Similarly, for females 20-24, the comparable figures were .704 and .703. These differences however are negligible and only occurred when inpatient data were used along with both outpatient and drug data.

When CRGs are compared to the ACRG3 level of aggregation, the results are again consistent with previous analyses. The predictive ratio tends to be slightly less accurate. For example, for all data sources, females 30-34 have a predictive ratio of .740 at the CRG level of aggregation and .737 for ACRG3. For males aged 45 – 49 the comparable figure are .995 and .982.

Predictive Ratio by Selected Diseases

Predictive ratios were also computed for specific diagnoses. These diagnoses were chosen based on sensitivity to the inclusion of drug data or general significance or interest. Diseases were defined as sets of related diagnoses. For each of the designated diseases, all enrollees who had either a single diagnosis associated with an inpatient admission, two outpatient diagnoses from different days, or were identified through prescription drug use, met the criteria for the inclusion in this part of the analysis. Appendix F identifies the diagnosis codes used for each disease group.

The identification of enrollees is clearly dependent upon the source of the data. While the largest number of enrollees are identified when all three types of data are used, the contribution of each source clearly varies. Of the three data sources, drug data identifies the most enrollees. Not surprisingly, inpatient data does not identify very many enrollees (See Table 14). This is especially so for the less serious illnesses such as migraines or hyperlipidemia which normally do not require a hospitalization. However, even for the most serious diagnoses this is also the case. Only 103 of 796 enrollees with (13%) Congestive Heart Failure are identified from inpatient data. For Breast Malignancies, the comparable figures are 90 cases out of 584 or 15%. For schizophrenia, less than 2% of the enrollees are identified. In part the

Age Category	Inpatient	Outpatient	Drug	Inpatient & Outpatient	Inpatient & Drug	Outpatient & Drug	Inpatient & Outpatient & Drug
Male							
< 5	1.575	1.365	1.266	1.375	1.286	1.223	1.229
5 - 9	2.133	1.842	1.784	1.835	1.740	1.655	1.651
10 - 14	1.702	1.492	1.424	1.488	1.394	1.338	1.334
15 - 19	1.548	1.330	1.277	1.332	1.261	1.201	1.205
20 - 24	2.020	1.723	1.606	1.725	1.577	1.497	1.494
25 - 29	1.882	1.677	1.551	1.663	1.528	1.478	1.472
30 - 34	1.565	1.448	1.361	1.442	1.349	1.318	1.314
35 - 39	1.298	1.243	1.198	1.239	1.190	1.168	1.169
40 - 44	1.123	1.124	1.104	1.126	1.097	1.097	1.097
45 - 49	0.920	0.973	0.989	0.975	0.992	0.991	0.995
50 - 54	0.713	0.823	0.841	0.821	0.858	0.879	0.876
55 - 59	0.612	0.748	0.763	0.756	0.790	0.812	0.820
60 - 64	0.523	0.691	0.683	0.691	0.721	0.758	0.758
65 +	0.438	0.649	0.644	0.657	0.678	0.727	0.726
Female							
< 5	1.813	1.545	1.543	1.549	1.529	1.440	1.448
5 - 9	2.516	2.114	2.049	2.107	2.017	1.885	1.881
10 - 14	1.884	1.637	1.566	1.633	1.534	1.464	1.463
15 - 19	1.307	1.161	1.159	1.162	1.144	1.109	1.109
20 - 24	1.014	0.913	0.933	0.915	0.920	0.888	0.887
25 - 29	0.744	0.710	0.720	0.714	0.707	0.704	0.703
30 - 34	0.758	0.738	0.745	0.741	0.741	0.739	0.740
35 - 39	0.806	0.826	0.826	0.825	0.827	0.846	0.845
40 - 44	0.772	0.830	0.874	0.828	0.869	0.891	0.891
45 - 49	0.683	0.786	0.832	0.781	0.830	0.872	0.870
50 - 54	0.607	0.746	0.835	0.748	0.838	0.888	0.885
55 - 59	0.555	0.718	0.783	0.722	0.806	0.848	0.853
60 - 64	0.506	0.719	0.724	0.710	0.756	0.811	0.805
65 +	0.475	0.690	0.702	0.700	0.746	0.816	0.819

Table 12. CRG predictive ratio by age and sex and data source

Age Category	Inpatient	Outpatient	Drug	Inpatient & Outpatient	Inpatient & Drug	Outpatient & Drug	Inpatient & Outpatient & Drug
Male							
< 5	1.558	1.401	1.265	1.404	1.258	1.223	1.226
5 - 9	2.140	1.930	1.841	1.919	1.806	1.767	1.758
10 - 14	1.713	1.558	1.475	1.551	1.450	1.429	1.424
15 - 19	1.561	1.362	1.300	1.367	1.290	1.235	1.238
20 - 24	2.016	1.741	1.610	1.743	1.585	1.517	1.516
25 - 29	1.881	1.677	1.557	1.670	1.535	1.477	1.476
30 - 34	1.561	1.453	1.367	1.448	1.354	1.320	1.317
35 - 39	1.299	1.246	1.197	1.244	1.188	1.168	1.168
40 - 44	1.125	1.128	1.101	1.130	1.097	1.098	1.098
45 - 49	0.918	0.973	0.971	0.976	0.972	0.980	0.982
50 - 54	0.709	0.805	0.818	0.807	0.835	0.850	0.851
55 - 59	0.611	0.737	0.733	0.741	0.761	0.793	0.797
60 - 64	0.518	0.670	0.650	0.673	0.682	0.729	0.734
65 +	0.438	0.627	0.609	0.634	0.642	0.710	0.710
Female							
< 5	1.810	1.587	1.567	1.586	1.547	1.483	1.484
5 - 9	2.515	2.183	2.099	2.172	2.063	1.973	1.966
10 - 14	1.893	1.675	1.604	1.670	1.578	1.520	1.516
15 - 19	1.314	1.179	1.188	1.178	1.172	1.133	1.132
20 - 24	1.013	0.914	0.944	0.914	0.927	0.896	0.894
25 - 29	0.751	0.709	0.728	0.711	0.720	0.707	0.708
30 - 34	0.761	0.729	0.752	0.732	0.747	0.738	0.737
35 - 39	0.805	0.813	0.832	0.813	0.830	0.840	0.839
40 - 44	0.774	0.818	0.869	0.816	0.865	0.881	0.878
45 - 49	0.684	0.772	0.822	0.771	0.826	0.853	0.852
50 - 54	0.605	0.725	0.833	0.726	0.844	0.868	0.869
55 - 59	0.548	0.700	0.775	0.700	0.797	0.831	0.832
60 - 64	0.500	0.683	0.711	0.678	0.734	0.779	0.780
65 +	0.478	0.654	0.657	0.670	0.702	0.759	0.770

Table 13. ACRG3 predictive ratio by age and sex and data source

Disease Group	Inpatient	Outpatient	Drug	Inpatient & Outpatient	Inpatient & Drug	Outpatient & Drug	Inpatient & Outpatient & Drug
Anxiety and Stress Diagnoses	41	455	10,055	482	10,074	10,329	10,344
Asthma	254	2,879	7,043	2,956	7,226	8,841	8,908
BPH	47	456	1,933	468	1,951	2,195	2,201
Breast Malignancy	90	584	0	584	90	584	584
Chronic Gastrointestinal Diagnoses	320	2,443	1,211	2,558	1,521	4,731	4,824
Congestive Heart Failure	103	204	658	234	718	776	796
Depression	105	781	7,934	863	8,009	8,437	8,497
Diabetes	251	2,689	3,959	2,746	4,008	4,461	4,478
Gynecological Diagnoses	741	5,901	14,078	5,990	14,643	18,726	18,787
Hyperlipidemia	53	2,501	9,704	2,541	9,725	10,595	10,614
Hypertension	530	7,681	21,184	7,802	21,348	23,172	23,222
Migraine	55	1,060	3,575	1,083	3,599	4,050	4,062
Schizophrenia	12	13	642	21	644	648	650

Table 14. Frequency by disease group and data source

Disease	Count	Inpatient	Outpatient	Drug	Inpatient & Outpatient	Inpatient & Drug	Outpatient & Drug	Inpatient & Outpatient & Drug
Anxiety and Stress Diagnoses	10,344	0.4525	0.7732	0.6359	0.7713	0.6908	0.7982	0.8132
Asthma	8,908	0.5431	0.7550	0.8875	0.7717	0.9011	0.9835	0.9898
BPH	2,201	0.7319	0.7888	0.6862	0.7999	0.7421	0.8466	0.8563
Breast Malignancy	584	0.7456	0.8697	0.0000	0.9380	0.7251	0.9180	0.9754
Chronic Gastrointestinal Diagnoses	4,814	0.4972	0.6136	0.7867	0.6306	0.7568	0.7485	0.7622
Congestive Heart Failure	796	0.4455	0.7308	0.7900	0.7545	0.8347	0.9756	0.9963
Depression	8,497	0.5496	0.7537	0.8509	0.7591	0.8713	0.9562	0.9620
Diabetes	4,478	0.5464	0.7773	0.8585	0.7939	0.8943	0.9897	1.0006
Gynecological Diagnoses	18,787	0.4182	0.4875	0.8237	0.494	0.8463	0.8689	0.8739
Hyperlipidemia	10,614	1.0294	0.764	0.7450	0.7825	0.7899	0.8770	0.8924
Hypertension	23,222	0.5213	0.7239	0.8515	0.7509	0.8964	0.9769	0.9907
Migraine	4,062	0.5565	0.6268	0.7563	0.6436	0.7738	0.8322	0.8434
Schizophrenia	650	0.3438	0.4743	0.8552	0.4993	0.9180	0.9835	1.0146

Table 15. CRG predictive ratio by disease group and data source

weakness of the results for inpatient data reflects the population of enrollees analyzed. This population arguably consists disproportionately of individuals with less severe forms of these diseases. Enrollees with more advanced cases of congestive heart failure or schizophrenia are more likely to be hospitalized.

When the predictive ratios are reviewed at the CRG level, the predictive ratios become progressively more accurate as additional data is used for CRG assignment (See Table 15). This is to be expected as the accuracy of CRGs depends on the ability to identify chronic diseases. A more important distinction is the comparison of the inpatient and outpatient data with the inpatient and drug data. With the exception of breast malignancies, BPH and chronic anxiety and stress diagnoses, the combination of inpatient and drug data is more accurate (closer to 1.00) than the combination of inpatient and outpatient data. Breast malignancy, reflects the fact that drug information does not identify any breast malignancy cases. Another distinction is that CRGs tends to work better with more significant illnesses. For example, when all three data sources are included, diabetes has a predictive ratio of 1.001 and congestive heart failure a predictive ratio of 0.996. This contrasts with predictive ratios of 0.791 for chronic anxiety and stress diagnoses and 0.843 for migraines. This, too, is to be expected. CRGs are more sensitive to more serious illnesses which tend to dominate an individual's need for medical care. Less serious illnesses such as chronic anxiety and stress diagnoses and migraines are often times not the most significant medical problem in an individual's life. This is reflected in the predictive ratios.

When the predictive ratio analysis is repeated for the ACRG3 level of aggregation, the predictive ratios become less accurate (See Table 16). This is to be expected as the loss of specificty, in this case due to the aggregation of CRGs, will result in the reduction of predictive accuracy.

Summary

Incorporating pharmacy data into CRGs greatly increases the observed prevalence of chronic and recent significant acute diseases. When only inpatient data are used in assigning CRGs, 98.1% of enrollees are categorized as healthy. When outpatient data are included, the percentage of enrollees categorized as healthy decreases to 79.7%. Adding drug data further decreases the percentage of enrollees categorized as healthy to 59.2%. If drug data are used in lieu of outpatient data and in combination with inpatient data, 66.7% of enrollees do not have any observed health problems. In short, drug data greatly improves the identification of individuals with chronic diseases or on-going significant acute health problems.

Some form of stop loss will always be part of any operational capitated payment system. With a $50,000 cap, pharmacy data greatly improved on inpatient only data (R^2 of 14.68% vs. 8.44%) but did not equal inpatient and outpatient data (R^2 of 16.91%). The most powerful model included data from all three sources (R^2 of 18.42%).

Disease	Count	Inpatient	Outpatient	Drug	Inpatient & Outpatient	Inpatient & Drug	Outpatient & Drug	Inpatient & Outpatient & Drug
Anxiety and Stress Diagnoses	10,344	0.4423	0.6713	0.6278	0.6778	0.6722	0.7708	0.7826
Asthma	8,908	0.6458	0.9700	1.0537	0.9780	1.0638	1.1505	1.1536
BPH	2,201	0.6461	0.6701	0.6527	0.6888	0.6898	0.7922	0.7959
Breast Malignancy	584	0.3050	0.5098	0.0000	0.5506	0.4441	0.6583	0.6978
Chronic Gastrointes-tinal Diagnoses	4,824	0.4139	0.5291	0.7688	0.5489	0.7230	0.7009	0.7104
Congestive Heart Failure	796	0.4714	0.6906	0.8242	0.7101	0.8681	1.0065	1.0141
Depression	8,497	0.5376	0.7331	0.8620	0.7328	0.8786	0.9523	0.9553
Diabetes	4,478	0.4655	0.7137	0.8552	0.7299	0.8837	0.9754	0.9829
Gynecological Diagnoses	18,787	0.5335	0.6648	0.8774	0.6484	0.8972	0.9711	0.9739
Hyperlipidemia	10,614	0.6891	0.7009	0.7259	0.7121	0.7547	0.8425	0.8497
Hypertension	23,222	0.3969	0.7008	0.8575	0.7120	0.8879	0.9568	0.9660
Migraine	4,062	0.4425	0.5171	0.6935	0.5277	0.7082	0.7614	0.7678
Schizophrenia	650	0.4840	0.6404	1.0138	0.6882	1.0637	1.1201	1.1468

Table 16. ACRG3 predictive ratio by disease group and data source

The analysis of predictive ratios offered few surprises. As is common with predictive ratios and risk adjusters such as CRGs, the tendency is to overestimate the expenditures of the healthy and underestimate those of the sick. This was apparent in the analysis of expenditure quintiles and demographic factors. The analysis of disease produced a somewhat unexpected result. Whereas. inpatient and outpatient data produced a higher R^2, the predictive ratios for the disease groups were more accurate (closer to 1.00) for inpatient and drug data. The only exception to this was breast malignancies, a set of diagnoses for which the drug data did not identify any additional cases.

Conclusion

CRGs were designed as a tool with three purposes, (1) retrospective population management, (2) risk adjustment, and (3) case identification for case management programs. Data from pharmacy programs would be useful for all three either as a substitute for outpatient data or as an adjunct to inpatient and outpatient data. The strength of pharmacy data lies in its ability to identify additional significant health problems beyond those reported on submitted claims and to identify those individuals whose conditions are more serious than can be communicated by an ICD-9-CM code. The utility of pharmacy data especially for population management and risk adjustment lies in it ability to reduces the "noise" of treated but unreported illnesses. This can be seen in the identification of additional cases, higher R^2, and more precise predictive ratios. For example, the inclusion of pharmacy data resulted in an increase of over 15,000 identifiable cases of hypertension, a threefold

increase. Therefore, pharmacy data can help give a more accurate epidemiological portrait of a population and provide the basis for better informed decisions.

The CRG model provides the framework for prospective and retrospective applications. CRGs with its clear and unambiguous categories can link individual medications, combinations of medications, and factors such as the duration of treatment to specific diseases. Equally important, it differentiates the severity of those diseases. For example, the medications associated with a specific illness (e.g., diabetes) or combination of illnesses (e.g., diabetes and hypertension) can be identified. This identification can be used prospectively to set appropriate levels of reimbursement and identify individuals who might benefit from more aggressive case management. It can also be used retrospectively, to profile a physician's patients and practice patterns. Moreover, the establishment of a link between specific diagnoses and specific drugs or combinations of drugs creates a significant opportunity for creating the basis of defining appropriate pattern of pharmacy utilization which in turn can help provide a clinical basis for managing pharmaceutical costs.

Pharmacy data, however, has clear limitations. As pointed out earlier it is no panacea. For example there are no defining drug therapies for a number of diagnoses. Then too, there are issues regarding variations in practice patterns, off-label use, limitations of pharmacy benefits, etc. There are ramifications to using what is essentially a procedure. (i.e., drug therapy) to categorize enrollees for the purpose of determining reimbursement levels. Although the current CRG methodology makes use of procedures, that use is judicious and limited. The procedures that are used are either so expensive (e.g., coronary bypass), profound (e.g., amputations), or limited in scope (e.g., wheelchairs) so as not to provide a real incentive for their use. A significant broadening the use of procedures, including drug therapies, would be problematic because of the possibility of offering incentives for aggressive treatments which might not be clinically justifiable. Pharmaceuticals are especially problematic in this regard. While some drugs are extremely expensive, many individual drugs (e.g., nitroglycerine) are not. Building them into a reimbursement model would certainly encourage their use. Any implementation of a pharmacy based reimbursement system must address this potential problem.

Limitations aside, pharmacy data has much to offer. Clearly care must be taken prior to incorporating it into a population management or risk adjustment methodology so as not to introduce undesirable incentives. But, its potential can be seen in this analysis. In what has essentially been a proof of concept analysis, pharmacy data was shown to be a valuable addition to CRGs. Pharmacy data was shown to be a reasonable alternative to outpatient data and a useful adjunct to inpatient and outpatient data.

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Research Report

Insight into Two Analytical Challenges for Disease Management

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Insight into Two Analytical Challenges for Disease Management

INTRODUCTION AND BACKGROUND

Escalating healthcare costs are causing employers and insurers to reevaluate the value and effectiveness of their medical management programs in order to reduce claims cost. Many organizations are looking to disease management (DM) programs to help cut medical costs and improve member satisfaction. The lack of standard accepted analytical methods for evaluating cost savings due to DM programs, combined with complex analytical and actuarial issues, has resulted in few credible benchmarks for savings attributable to DM programs.

Several publications have helped to clarify the state of DM outcomes measurement today. The Washington Business Group on Health notes that although standards for accrediting and certifying DM programs exist, it will take several years before they make an impact on the industry.[i] Although the AAHP/HIAA found no DM evaluation met the gold standard of randomized, controlled study, it reported all DM evaluations studied used valid, non-experimental methods.[ii] Another recent publication, *Disease Management: The Programs and the Promise*[iii] provided a summary of self-reported measurement practices gathered from 14 DM companies. It also provided a summary of recent publications regarding DM. The 2002 report *Standard Outcome Metrics and Evaluation Methodology for Disease Management Programs*[iv] raised some key issues in DM and proposed a methodology for standardizing outcomes measurement.

Despite these efforts, we believe significant actuarial issues continue to confound analysis of savings from DM, including:

- *Regression to the mean:* Members recruited into a DM program during a high point of individual medical utilization and cost (e.g., post-hospitalization) typically return to lower levels of utilization and cost due to the natural course of the underlying disease processes. This trend occurs with or without active intervention by a DM program.

- *Selection bias:* Members in a DM program may be different than members not participating in the DM program. This may result in significant utilization and cost differences between those enrolled and not enrolled in a DM program.

We believe that data presented in this report helps put these actuarial and analytical issues into perspective.

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i Washington Business Group on Health Institute on Heal Care Costs and Solutions. *Disease Management.* Issue Brief. Vol. 1/No. 1. July/August 2002.

ii American Association of Health Plans/Health Insurance Association of America. *The Cost Savings of Disease Management Programs: Report on a Study of Health Plans.* November 2003.

iii Johnson, Alison. Milliman Research Report *Disease Management: The Programs and the Promise.* May 2003.

iv American Healthways, Johns Hopkins. *Standard Outcome Metrics and Evaluation Methodology for Disease Management Programs.* 2nd Annual Disease Management Outcomes Summit, November 7 – 10, 2002, Palm Desert, CA

RESEARCH OBJECTIVES

Our goals are to present data on two large publicly available databases and discuss the implications of regression to the mean and selection bias in DM medical cost savings calculations. Our research is intended to present typical cost patterns in a US population. The data may or may not represent a typical DM population. These data provide insight into:

- Medical cost trends following an event that may trigger initiation of DM
- Variation in the medical cost of populations that may opt in or out of DM programs
- Cost patterns in the terminally ill and potentially high-cost segment of a disease population
- Difference in cost between patients with and without comorbidities

This report provides information for the following disease states commonly addressed by DM programs:

- Diabetes only
- Coronary Artery Disease (CAD) only
- Congestive Heart Failure; with or without CAD (CHF)
- Comorbid Diabetes: Diabetes and any combination of the above disease states

Medical Cost Trend Analysis

We analyze the cost of populations before and after a "significant event," either an emergency room visit or an acute inpatient admission. Some DM program savings calculations compare costs experienced after implementing the DM program with costs from the period prior to implementation (pre-implementation to post-implementation comparison.) For DM programs enrolling the DM population after a significant event, all or a portion of reported "savings" could be attributed to regression to the mean.

Population Analysis

We analyze compliant and non-compliant populations. DM programs aim to improve health status by improving patient management and compliance. People participating in a DM program may be more motivated to improve their health status than those unwilling to participate. If people enrolling in DM are more compliant, and the cost of compliant people is different, the selection bias will result in the population in DM having lower or higher cost than the population not in DM.

Selection bias may be introduced into DM analysis in a variety of ways. DM programs often target chronic progressive diseases and may appropriately exclude certain high-risk low-return individuals from either the DM program or from their savings analyses. These excluded individuals may have such severe diseases that despite proactive management, their healthcare costs rise. We analyze cost in a commonly excluded segment of the population, the terminally ill and those with malignant cancer or transplants, to demonstrate the potential impact of excluding or including this population in DM programs or DM program analysis.

ACTUARIAL AND ANALYTICAL ISSUES IN DISEASE MANAGEMENT

DM programs target different populations and interventions and use different methodologies to calculate claims cost savings as demonstrated in Johnson's survey results[v]. This lack of consistency in program structures contributes to a dearth of widely accepted data substantiating cost savings resulting from DM. Following is a discussion of some additional factors, which should be considered in DM savings calculations.

Provider reimbursement: In most health plans, provider reimbursement is dynamic. Some provider reimbursement changes are accounted for through average medical cost trends in the general population. However, applying an average health plan trend rate to a specific DM population may not account for all provider reimbursement changes. The DM population may access certain providers or provider types differently from the overall health plan. Since reimbursement for all providers does not change at the same rate or at the same time, provider reimbursement changes producing a small effect on overall trend may generate a significant effect in the DM population.

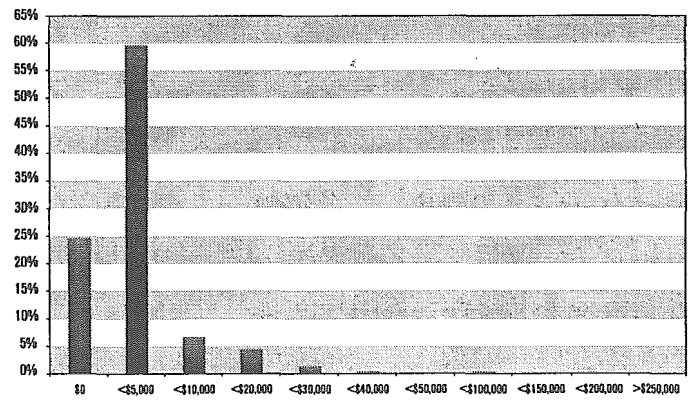
Benefit design: Benefit design changes affect medical cost and medical cost trends. All benefit design changes add or remove some healthcare services from the medical cost calculation. Benefit design changes may also alter patient mix by attracting certain types of members.

Some benefit changes are accounted for through average medical cost trends in the general population. However, some benefit design changes may affect medical cost for the DM population differently than the population not under DM.

Patient mix: Not all people with the same condition cost the same amount, as demonstrated in Figure 1, which illustrates the claims distribution of a typical commercially insured population. Patient mix can change from year to year; usually due to changes in health plan choices, local market conditions (e.g., change in employer), benefit design, and premium.

FIGURE 1

CLAIMS DISTRIBUTION OF A TYPICAL COMMERCIAL POPULATION



Severity adjustment tools may accurately reflect the presence of a particular disease state but may not be able to accurately account for the severity of illness of persons with the disease state. For example, severity adjustment tools will almost always account for the presence of CHF in a population; however, they may not be able to differentiate a more severely ill class IV CHF patient from a less severely ill class III CHF patient. Therefore, a DM program experiencing a significant slowing in enrollment growth may have an undetectable change in the mix of CHF patients from less severe to more severe due to the progressive nature of CHF.

v Johnson, Alison.

Change in patient mix may also cause a change in observed patient mortality, which can have a significant affect on medical cost. Although people who die may incur high medical cost prior to their demise, total lifetime cost may be higher in patients who survive.

Claims adjudication: Any change in a health plan's claims adjudication processes can affect medical cost calculations. Changes in timeliness of payment, procedure coding (such as the introduction of new codes), or modification in payment rules can produce significant changes in medical cost unrelated to patient care. A DM population may use the services undergoing change more than other populations.

Health cost trend: Health cost trend is affected by multiple factors. In a given year, some factors may affect a particular disease state more than others. Some examples of events affecting health costs for coronary artery disease and not the health costs for asthma are:

- New technology: the introduction of drug eluting stents
- New information about existing technology: the value of certain drugs like ACE Inhibitors post-heart attack
- Industry changes: change from brand to generic cholesterol-lowering agents
- Changes in medical practice: change in recommendations on use of cholesterol-lowering agents

Technical methodology: In addition to the considerations listed above, there are many technical methodology choices an analyst can make regarding the populations and claims included in a DM medical cost analysis. Among other methodological considerations, any DM analysis should clearly state the approach regarding the following:

TABLE 1

Population Issues	Claims Issues
Outlier inclusion/exclusion	All claims or just disease related claims
Criteria for health plan enrollment during the measurement period (e.g., continuous)	People with the targeted condition or populations in the DM program
Limits on time in the DM program	Analytical time period:
Limits on time enrolled in the health plan prior to enrollment in the DM program	*From:* significant event or acceptance into the program or calendar year
	To: end of DM services or calendar year

American Healthways and Johns Hopkins[vi] proposed a standardized pre-intervention post-intervention methodology. Johnson surveyed health plans on their use of three outcomes measurement methods (1) pre-enrollment to post-enrollment comparison, (2) control group comparison, and (3) comparison of requested to approved services. Most survey respondents used method (1).[vii]

vi American Healthways, Johns Hopkins
vii Johnson, Alison.

Following is an illustrative example of the methodology used by a typical DM program to identify participatory members:

Identification Criteria

Members meeting diagnosis or procedure codes criteria are included in a DM program unless they meet specific "exclusionary criteria" specified below. The time period used to identify such members is 12 months prior to program initiation. The participation criteria include identifying members based on trigger events such as hospital admissions. Members are admitted in the following disease management programs: Congestive Heart Failure, Coronary Artery Disease, Diabetes, COPD, and Asthma.

The initial identifying event determines the disease program for that member and that member remains in that program for savings calculation purposes regardless of subsequent activity.

Exclusionary Criteria

- Members with ESRD, AIDS, metastatic cancer, malignant cancer, requiring transplants, or those who have had one in the past 12 months
- Members in a nursing facility, with no telephone access or with severe psychological problems

Compensation Calculation

Savings are defined as the difference between the actual cost of members during the program and pre-implementation (baseline) period. The baseline costs are trended for, among others, medical inflation, utilization, and benefit changes at an agreed upon rate. The difference between the baseline amount and the post-implementation actual program cost is the amount saved by the health plan. The DM vendor will be paid X% of the total savings.

For example:

TABLE 2

????

Time Post Trigger Event	Risk Member Months	Baseline Per Patient Per Month Cost	Pre-Implementation Baseline Cost ($000)	Post-Implementation Cost ($000)	Program Savings ($000)	Amount Owed to DM Vendor ($000)
1	500	$2,400	$1,200	$900	$300	$75
2	600	$2,300	$1,380	$800	$580	$145
3	700	$2,500	$1,750	$700	$1,050	$263
4	800	$2,200	$1,760	$600	$1,160	$290
			$6,090	**$3,000**	**$3,090**	**$773**

The significance of the various analytical issues differs by the type of analysis and the population measured. We present the most common analytical methods and related confounding issues in Table 3.

TABLE 3

Analytical Issues		
Method	Population Measured	Confounding Analytical Issues
Pre-intervention to post-intervention comparison	Anyone with the targeted condition	Provider reimbursement Benefit design Patient mix Claims adjudication Health cost trend
	Anyone participating in the DM program	Regression to the mean Provider reimbursement Benefit design Patient mix Claims adjudication Health cost trend
Intervention to control comparison	Matched cohorts	Selection bias Provider reimbursement Patient mix

DISEASES INCLUDED IN STUDY

Understanding the disease process is critical to understanding DM program analytical issues and results.

Diabetes

Medical services for diabetics include management of the disease process itself as well as neurological, peripheral vascular, cardiovascular, renal, and other complications. Although Type I and Type II diabetes are different in many respects, they are treated similarly in DM programs. DM attempts to stem costs of the population by appropriate treatment and prevention of complications or complication progression through improvement in compliance with self-care (e.g., diet, medications) and recommended routine medical care (e.g., eye and foot exams).

Most diabetes-related significant events are due to complications of diabetes rather than the disease itself. Patients become increasingly symptomatic and require interventions such as dialysis or surgery to improve peripheral circulation, which generate high healthcare costs. For many diabetic complications there is no resolution, although there may be an improvement in pre-event symptoms. Compared to pre-event, post-event treatment may involve higher drug costs, more office visits, periodic diagnostic testing, and other therapies. Complicated diabetic patients may continue to have subsequent significant events.

Coronary Artery Disease

The population affected by CAD is largely older. DM attempts to manage costs of the CAD population by appropriate treatment and slowing the progression of the disease through improved compliance with self-care (e.g., diet, exercise, medications) and recommended routine medical care (e.g., cholesterol testing).

CAD can block the arteries providing blood to the heart. Patients with CAD can become increasingly symptomatic and require surgical interventions such as bypass surgery that generate high healthcare costs. After recovery from the significant event, the majority of CAD patients have the immediate problem corrected or under better control. Compared to pre-event, post-event therapy may involve higher drug costs, more office visits, and possibly periodic diagnostic testing. Most CAD patients will not have a subsequent significant event for several years.

Congestive Heart Failure

CHF is a chronic progressive disease. CHF affects an older population. DM attempts to manage costs of the CHF population by slowing the progression of the disease through improved compliance with self-care (e.g., diet, weight monitoring, medications) and recommended routine medical care (e.g., physician follow up).

CHF occurs with decreased ability of the heart to pump blood throughout the body. Retention of fluid causes difficulty breathing among other symptoms. Patients with CHF can become increasingly symptomatic and require acute care. Exacerbation of symptoms is common with dietary non-compliance and worsening heart function. Most exacerbations are treated medically. Because the precipitating cause of the exacerbation may be left unmanaged and heart function continues to worsen, most CHF patients require periodic acute care. Compared to pre-event, post-event therapy may involve higher drug costs, more office visits, and possibly periodic diagnostic testing.