



A new generation of Health Actuary?

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Introductions

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Strong research foundation. Author of a number of peer-reviewed papers and 3 books (including 2 on the SOA health syllabus). Since 2010, Vice President and head of Research, Walgreen Cos., Chicago. Responsible for all Clinical Research of this Fortune 30 healthcare company.

Visiting Professor, Dept. of Probability and Applied Statistics, University of California, Santa Barbara and Adjunct Research Professor, Georgetown University Dept. of Health Administration.

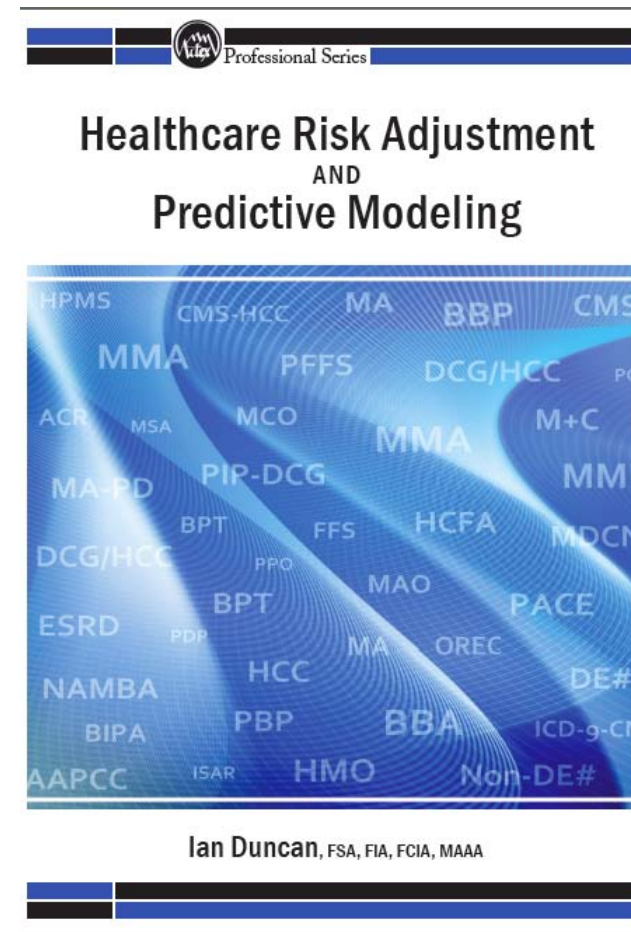
Introductions

Author of several books and peer-reviewed studies in healthcare management and predictive modeling.

Published 2008



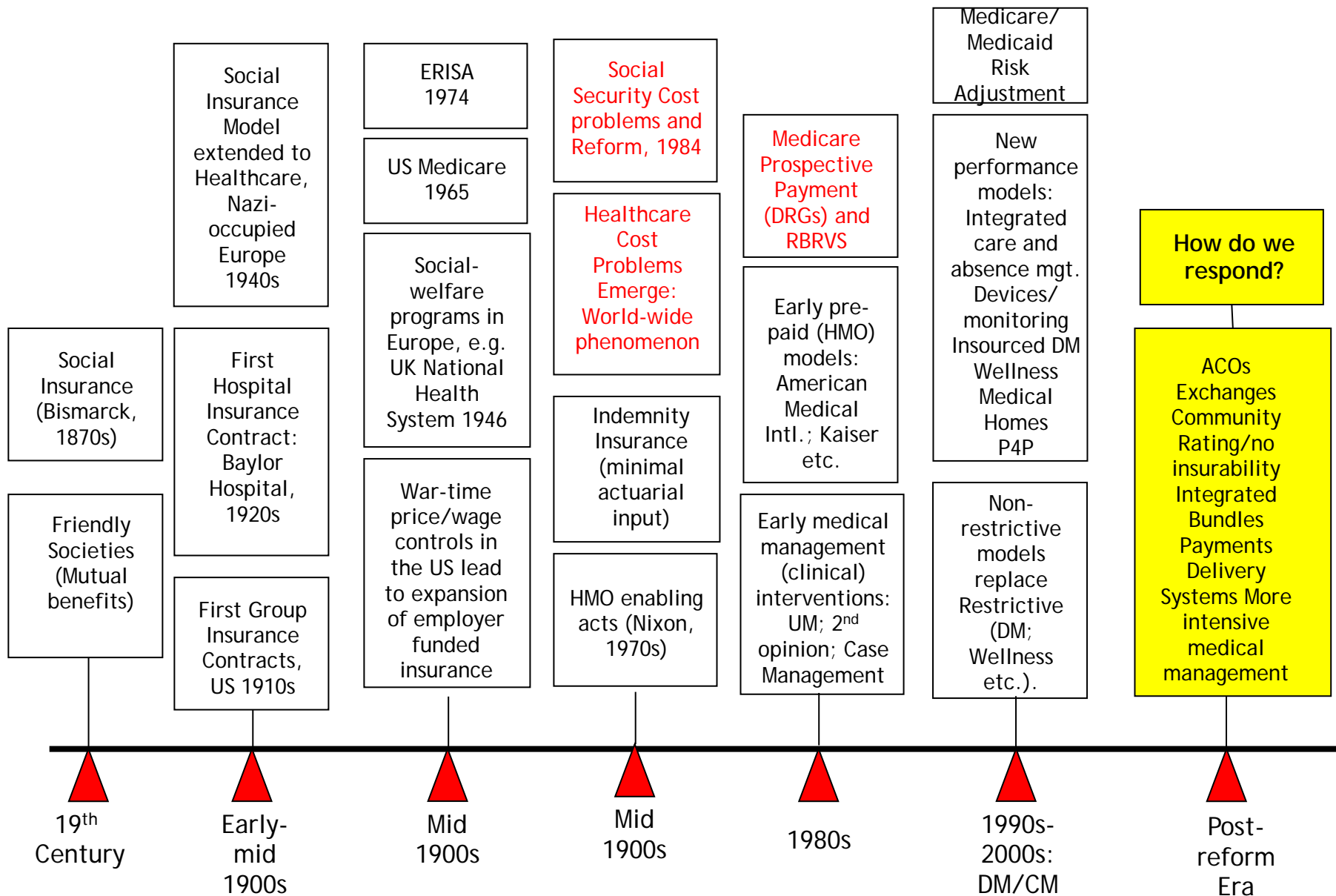
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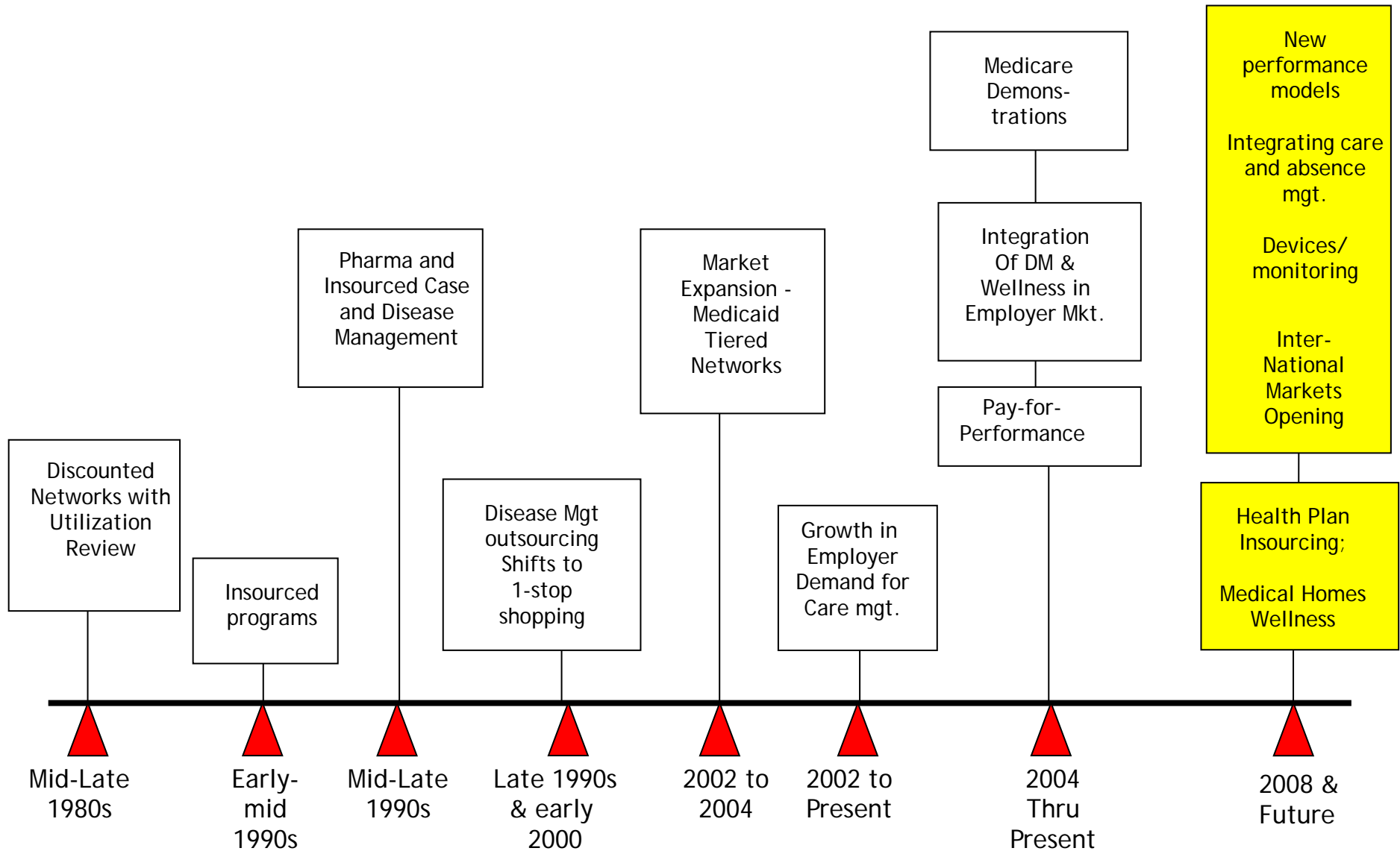
Agenda

1. Health insurance and health actuarial history.
2. Traditional Health Actuarial Skills.
3. The new world of Healthcare Actuarial Science.
4. Discussion.

Evolution of Health Insurance



Evolution of Managed Care



Healthcare Actuaries

What skills were necessary to be a healthcare actuary in the 1970s and 1980s?

1. Understanding of risk: it has always been the province of the actuary to understand and to be able to price risk. Health Insurance was no exception:
 - Rate setting
 - Underwriting (including financial underwriting of groups)
 - Capital Requirements (RBC)
2. As regulation increased, an understanding of regulations, e.g.:
 - Small group reform;
 - Medicare Advantage;
 - Medicare Part D;
 - Various state requirements);

Our value has always been in taking a cold, hard look at risk, being able to price it, and being able to assess the relative risks represented by different groups and individuals.

New demands on Health Actuaries

As health insurance has changed, so have demands on health actuaries.

Our review of the history of US Health Insurance shows that, to control costs, payers have increasingly had to turn to Medical Management interventions. This creates many opportunities for actuaries:

1. The value of medical management: medical management comes in multiple formats and flavors. No two patients are alike; no two programs have the same results. Many (exaggerated) claims are made for medical management. Actuaries, as trusted financial advisors, are increasingly becoming involved in *Program Evaluation*.
2. Pricing: the results of medical management programs often have to be translated into *pricing* for customers and employers.
3. Contracting (including new forms, such as pay-for-performance): the patient is increasingly being steered to use more “efficient” providers, who are rewarded for their efficiency.

New demands on Health Actuaries (contd.)

To respond to the new demands for actuaries to contribute to managed care, new skills are required:

1. Clinical: the old-style actuary had no need to understand diseases such as diabetes, or their treatments. Now, it is necessary to understand diseases, treatments, programs and detailed codes for identifying diseases from data.
2. Members: the old-style actuary may have priced groups without considering the clinical make-up of the group. Now, actuaries are increasingly taking a *population health* approach (e.g. how much resource should an average diabetic consume?)
3. Providers: the old-style actuary probably assisted with contract evaluation and negotiation. However, now the actuary must understand medical practice in order to translate this into financial terms (what is a provider's quality rating? What is it worth from a P-4-P or pricing perspective)?
4. Programs: what programs work and do not work? What vendors provide value for money?

New demands on Health Actuaries (contd.)

Healthcare Actuaries face not only clinical demands. There are also new analytical demands.

1. Risk Adjustment: risk adjustment was introduced in the 1990s and has become something of a “silver bullet” in terms of the thinking of policy-makers who do not understand that risk adjustment does not *manage* risk, it merely shifts dollars around the system. The higher profile accorded to risk adjustment by government entities and by the PPACA makes this an essential tool for the new healthcare actuary.
2. Predictive modeling: a close cousin of Risk Adjustment, Predictive Modeling has many flavors, all of which have to do with identifying and stratifying members of a population.
3. Healthcare Analytics: Risk Adjustment and Predictive Modeling are examples of a broader class of healthcare analytics made capable by more robust tools and data resources.

21st Century Health Actuary Tool-kit

Everything you learned from the FSA exams, plus:

1. Clinical knowledge (diseases, therapies, programs).
2. As part of an understanding of diseases and therapies, knowledge of evidence-based medicine and quality measures (HEDIS/STARS).
3. Clinical programs (disease management, case management, wellness etc.).
4. Detailed healthcare data, including condition and severity identification from medical claims, laboratory test values, prescription drugs, etc.
5. Analytical systems (SQL/SAS).
6. Analytical tools:
 - Risk Adjustment
 - Gaps-in-care
 - Data Mining (predictive modeling)
7. Program evaluation techniques.
8. Healthcare Economics.
9. Comparative Effectiveness studies.

What is health risk?

Risk is a combination of two factors: **loss** and **probability**:

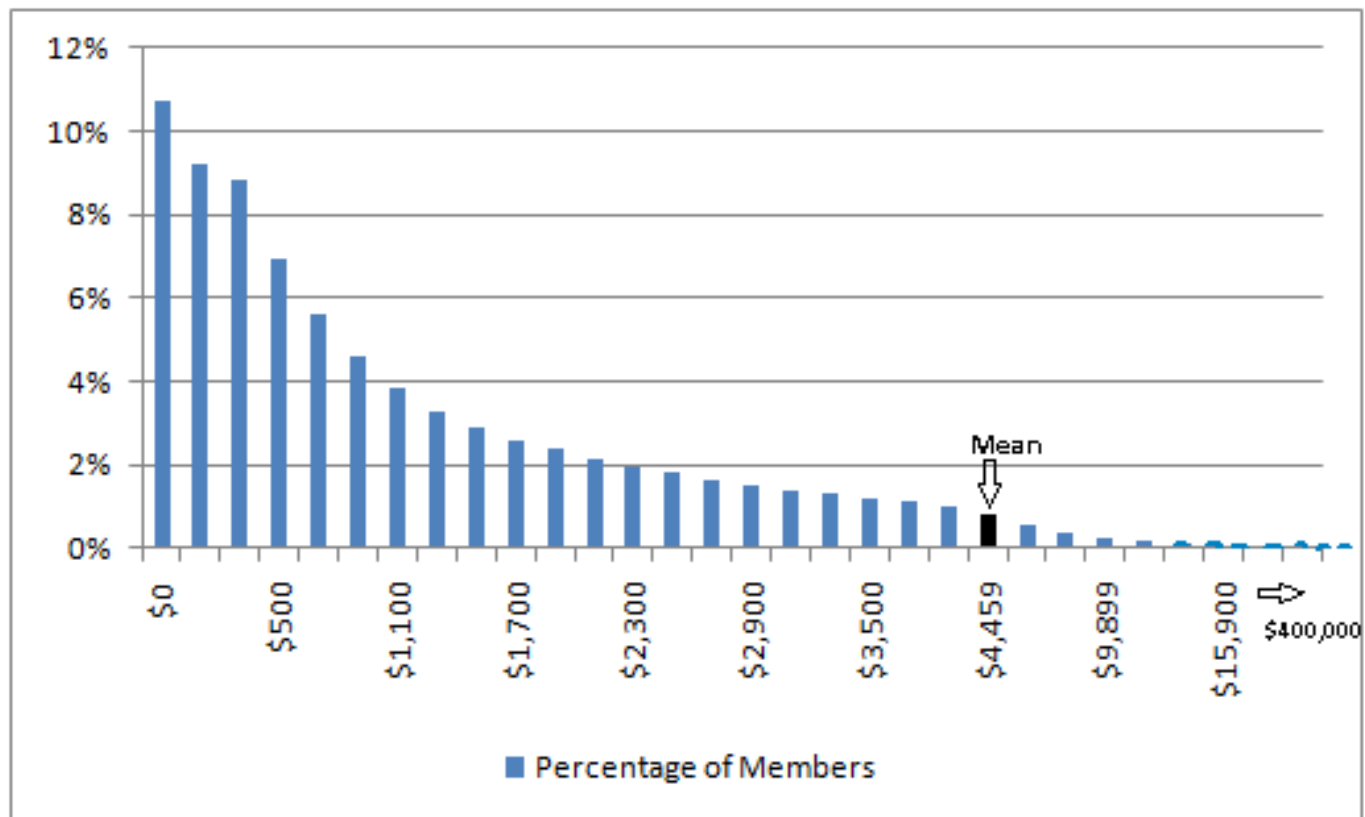
$$\mathbf{Risk = F (Loss; Probability)}$$

Risk Prediction in healthcare is all about identifying and predicting losses.

Risk Management in Healthcare is about managing loss **frequency** and **severity**.

Typical Distribution of health cost

Health cost (Risk) is typically highly-skewed. The challenge is to predict the tail*.



* Distribution of allowed charges within the Solucia Consulting database (multi-million member national database).

Traditional (actuarial) Risk Prediction

Age/Sex: although *individuals* of the same age and sex represent a range of risk profiles and costs, *groups* of individuals of the same age and sex categories follow more predictable patterns of cost. The majority of non-Government healthcare is financed by employer groups.

Relative Cost PMPY by Age/Sex			
	Male	Female	Total
< 19	\$1,429	\$1,351	\$1,390
20-29	\$1,311	\$2,734	\$2,017
30-39	\$1,737	\$3,367	\$2,566
40-49	\$2,547	\$3,641	\$3,116
50-59	\$4,368	\$4,842	\$4,609
60-64	\$6,415	\$6,346	\$6,381
Total	\$2,754	\$3,420	\$3,090

Typical Age/Sex Prediction (Manual Rating)

Age/Sex: Relative costs for different age/sex categories can be expressed as relative risk factors, enabling us to assess the “average” risk of an individual, or the overall (relative) risk of a population.

Relative Costs Using Age/Sex Factors					
	Male Risk Factor	Male Number	Female Risk Factor	Female Number	Weighted Number
< 19	0.46	4	0.44	12	7.12
20-29	0.42	12	0.88	19	22.00
30-39	0.56	24	1.09	21	36.33
40-49	0.82	30	1.18	24	52.92
50-59	1.41	15	1.57	12	39.99
60-64	2.08	3	2.05	1	8.29
Total	0.89	88	1.11	89	166.65
Relative age/sex factor					0.94

Accuracy of Traditional Risk Prediction

Traditional (Age/Sex) risk prediction is somewhat accurate at the population level. Larger group costs are more predictable than smaller groups.

Demographic Factors as Predictors of Future Health Costs

Employer	Number of lives	Age/Sex Factors		Factor Ratio	Predicted Cost*	Actual Cost	Difference** (Predicted-Actual)	
		Baseline	Subsequent Year	Subsequent / Average			\$	%
1	73	1.37	1.42	138%	\$4,853	\$23,902	(\$19,049)	-392.5%
2	478	0.74	0.76	74%	\$2,590	\$2,693	(\$102)	-3.9%
3	37	0.86	0.87	84%	\$2,965	\$1,339	\$1,626	54.8%
4	371	0.95	0.97	95%	\$3,331	\$3,325	\$6	0.2%
5	186	1.00	1.03	100%	\$3,516	\$3,345	\$170	4.8%
6	19	1.80	1.85	180%	\$6,328	\$10,711	(\$4,383)	-69.3%
7	359	0.95	0.97	94%	\$3,315	\$3,401	(\$87)	-2.6%
8	543	0.94	0.96	93%	\$3,269	\$3,667	(\$398)	-12.2%
9	26	1.60	1.64	159%	\$5,595	\$5,181	\$414	7.4%
Average		1.00	1.03	1.00	\$3,520	\$3,520	\$ -	0.0%
Sum of absolute Differences (9 sample groups only)							\$26,235	

Prior Experience adds to accuracy

To account for the variance observed in small populations, actuaries typically incorporate prior cost into the prediction, which adds to the predictive accuracy. A “credibility weighting” is used. Here is a typical formula:

$$\text{Expected Cost} = \text{Prior Year Cost} \times \text{Trend} \times Z + \text{Book of Business Cost} \times (1 - Z)$$

where $Z = \left(\frac{N}{1000}\right)^{0.5}$ and N is the number of members in the group.

Combination of Age, Sex, and Prior Cost as a Predictor of Future Experience.							
Employer	No. of lives	Credibility Factor	Cost PMPY			Difference vs. Actual	
			Baseline	Subsequent Year Pre-dicted	Subsequent Year Actual	Difference	Difference (% of Actual)
1	73	0.19	\$27,488	\$9,908	\$23,902	(\$13,994)	-141.2%
2	478	0.49	\$1,027	\$2,792	\$2,693	\$100	3.6%
3	37	0.14	\$1,050	\$2,724	\$1,339	\$1,385	50.9%
4	371	0.43	\$2,493	\$3,119	\$3,325	(\$205)	-6.6%
5	186	0.30	\$3,377	\$3,617	\$3,345	\$271	7.5%
6	19	0.10	\$11,352	\$6,971	\$10,711	(\$3,739)	-63.6%
7	359	0.42	\$2,008	\$2,880	\$3,401	(\$522)	-18.1%
8	543	0.52	\$2,598	\$3,108	\$3,667	(\$559)	-18.0%
9	26	0.11	\$3,022	\$5,350	\$5,181	\$169	3.2%
...
Average			\$3,090	\$3,520	\$3,520	\$ 0	0%
Sum of absolute Differences (9 sample groups only)						\$20,944	

What does Clinical information tell us about risk?

Having information about a patient's condition, particularly chronic condition(s) is potentially useful for predicting risk.

Condition-Based Vs. Standardized Costs						
Member	Age	Sex	Condition	Actual Cost (Annual)	Standardized Cost (age/sex)	Condition-Based Cost/ Standardized Cost (%)
1	25	M	None	\$863	\$1,311	66%
2	55	F	None	\$2,864	\$4,842	59%
3	45	M	Diabetes	\$5,024	\$2,547	197%
4	55	F	Diabetes	\$6,991	\$4,842	144%
5	40	M	Diabetes and Heart conditions	\$23,479	\$2,547	922%
6	40	M	Heart condition	\$18,185	\$2,547	714%
7	40	F	Breast Cancer and other conditions	\$28,904	\$3,641	794%
8	60	F	Breast Cancer and other conditions	\$15,935	\$6,346	251%
9	50	M	Lung Cancer and other conditions	\$41,709	\$4,368	955%

Risk Groupers predict relative risk

Commercial Risk Groupers are available that predict relative risk based on diagnoses. Particularly helpful for small groups.

Application of Condition Based Relative Risk						
			Cost PMPY		Difference (Predicted-Actual)	
Employer	Number of lives	Relative Risk Score	Predicted	Actual	\$	%
1	73	8.02	\$28,214	\$23,902	\$4,312	15.3%
2	478	0.93	\$3,260	\$2,693	\$568	17.4%
3	37	0.47	\$1,665	\$1,339	\$326	19.6%
4	371	0.94	\$3,300	\$3,325	(\$25)	-0.8%
5	186	1.01	\$3,567	\$3,345	\$222	6.2%
6	19	4.14	\$14,560	\$10,711	\$3,850	26.4%
7	359	0.84	\$2,970	\$3,401	(\$432)	-14.5%
8	543	0.80	\$2,833	\$3,667	(\$834)	-29.4%
9	26	1.03	\$3,631	\$5,181	(\$1,550)	-42.7%
Average						
			\$ -	0.0%	\$ -	0.0%
Sum of absolute Differences (9 sample groups only)					\$12,118	

Commercially-available Risk Groupers

Commercially Available Grouper Models		
Company	Risk Grouper	Data Source
CMS	Diagnostic Risk Groups (DRG) (There are a number of subsequent “refinements” to the original DRG model, which we discuss below.)	Hospital claims only
CMS	HCCs	Age/Sex, ICD -9
3M	Clinical Risk Groups (CRG)	All Claims (inpatient, ambulatory and drug)
IHCIS/Ingenix	Impact Pro	Age/Sex, ICD-9 NDC, Lab
UC San Diego	Chronic disability payment system Medicaid Rx	Age/Sex, ICD -9 NDC
Verisk Sightlines™	DCG RxGroup	Age/Sex, ICD -9 Age/Sex, NDC
Symmetry/Ingenix	Episode Risk Groups (ERG) Pharmacy Risk Groups (PRG)	ICD – 9, NDC NDC
Symmetry/Ingenix	Episode Treatment Groups (ETG)	ICD – 9, NDC
Johns Hopkins	Adjusted Clinical Groups (ACG)	Age/Sex, ICD – 9

Risk Groupers (2)

As an alternative to commercially-available risk groupers, analysts can develop their own models using common data mining techniques. Each method has its pros and cons:

There is a considerable amount of work involved in building algorithms from scratch, particularly when this has to be done for the entire spectrum of diseases. Adding drug or laboratory sources to the available data increases the complexity of development.

While the *development* of a model may be within the scope and resources of the analyst who is performing research, use of models for production purposes (for risk adjustment of payments to a health plan or provider groups for example) requires that a model be maintained to accommodate new codes. New medical codes are not published frequently, but new drug codes are released monthly, so a model that relies on drug codes will soon be out of date unless updated regularly.

Commercially-available clinical grouper models are used extensively for risk adjustment when a consistent model, accessible to many users, is required. Providers and plans, whose financial stability relies on payments from a payer, often require that payments be made according to a model that is available for review and validation. The predictive accuracy and usefulness of commercially available models has been studied extensively by the Society of Actuaries, which has published three comparative studies in the last 20 years.

Risk Groupers (3)

An analyst that builds his own algorithm for risk prediction has control over several factors that are not controllable with commercial models:

Which codes, out of the large number of available codes to recognize. The numbers of codes and their redundancy (the same code will often be repeated numerous times in a member record) makes it essential to develop an aggregation or summarization scheme.

The level at which to recognize the condition. How many different levels of severity should be recognized?

The impact of co-morbidities. Some conditions are often found together (for example heart disease with diabetes). The analyst will need to decide whether to maintain separate conditions and then combine where appropriate, or to create combinations of conditions.

The degree of certainty with which the diagnosis has been identified (confirmatory information). The accuracy of a diagnosis may differ based on who codes the diagnosis, for what purpose and how frequently a diagnosis code appears in the member record. The more frequently a diagnosis code appears, the more reliable the interpretation of the diagnosis. Similarly, the source of the code (hospital, physician, laboratory) will also affect the reliability of the diagnostic interpretation.

Data may come from different sources with a range of reliability and acquisition cost. A diagnosis in a medical record, assigned by a physician, will generally be highly reliable. Other types of data are not always available or as reliable.

Algorithm Development: Diabetes Example

Not all diabetics represent the same level of risk. Different diagnosis codes help identify levels of severity.

Codes for Identification of Diabetes Severity	
Diagnosis Code (ICD-9-CM)	Code Description
250.0	Diabetes mellitus without mention of complication
250.1	Diabetes with ketoacidosis (complication resulting from severe insulin deficiency)
250.2	Diabetes with hyperosmolarity (hyperglycemia (high blood sugar levels) and dehydration)
250.3	Diabetes with other coma
250.4	Diabetes with renal manifestations (kidney disease and kidney function impairment)
250.5	Diabetes with ophthalmic manifestations
250.6	Diabetes with neurological manifestations (nerve damage as a result of hyperglycemia)
250.7	Diabetes with peripheral circulatory disorders
250.8	Diabetes with other specified manifestations
250.9	Diabetes with unspecified complication

Algorithm Development: Diabetes Example

Relative Costs of Members with Different Diabetes Diagnoses			
Diagnosis Code ICD-9-CM	Description	Average cost PMPY	Relative cost
250	A diabetes diagnosis without a fourth digit (i.e., 250 only).	\$13,258	105%
250.0	Diabetes mellitus without mention of complication	\$10,641	85%
250.1	Diabetes with ketoacidosis (complication resulting from severe insulin deficiency)	\$16,823	134%
250.2	Diabetes with hyperosmolarity (hyperglycemia (high blood sugar levels) and dehydration)	\$26,225	208%
250.3	Diabetes with other coma	\$19,447	154%
250.4	Diabetes with renal manifestations (kidney disease and kidney function impairment)	\$24,494	195%
250.5	Diabetes with ophthalmic manifestations	\$11,834	94%
250.6	Diabetes with neurological manifestations (nerve damage as a result of hyperglycemia)	\$17,511	139%
250.7	Diabetes with peripheral circulatory disorders	\$19,376	154%
250.8	Diabetes with other specified manifestations	\$31,323	249%
250.9	Diabetes with unspecified complication	\$13,495	107%
357.2	Polyneuropathy in Diabetes	\$19,799	157%
362	Other retinal disorders	\$13,412	107%
366.41	Diabetic Cataract	\$13,755	109%
648	Diabetes mellitus of mother complicating pregnancy childbirth or the puerperium unspecified as to episode of care	\$12,099	96%
TOTAL		\$12,589	100%

Algorithm Development: Diabetes Example

Which leads to a possible relative risk severity structure for diabetes:

A Possible Code Grouping System for Diabetes			
Severity Level	Diagnosis Codes Included	Average Cost	Relative Cost
1	250; 250.0	\$10,664	85%
2	250.5; 250.9; 362; 366.41; 648	\$12,492	99%
3	250.1; 250.3; 250.6; 250.7; 357.2	\$18,267	145%
4	250.2; 250.4	\$24,621	196%
5	250.8	\$31,323	249%
	TOTAL (All diabetes codes)	\$12,589	100%

Algorithm Development: Diabetes Example

Example of an identification algorithm:

Example of a Definitional Algorithm			
Disease	Type	Frequency	Codes
Diabetes Mellitus	Hospital Admission or ER visit with diagnosis of diabetes in any position	At least one event in a 12-month period	ICD-9 codes 250, 357.2, 362.0, 366.41, 648.0
	Professional visits with a primary or secondary diagnosis of diabetes	At least 2 visits in a twelve month period	CPT Codes in range of 99200-99499 series E & M codes or 92 series for eye visits
	Outpatient Drugs: dispensed insulin, hypoglycemic, or anti-hyperglycemic prescription drug	One or more prescriptions in a twelve month period	Diabetes drugs (see HEDIS or similar list of drug codes).
EXCLUDE gestational diabetes.	Any (as above)	As above	648.8x

Commercial Groupers: SOA studies

There have been three Society of Actuaries studies of commercial risk grouper models published. All are available at www.soa.org.

Dunn DL, Rosenblatt A, Taira DA, et al. "A comparative Analysis of Methods of Health Risk Assessment." *Society of Actuaries (SOA Monograph M-HB96-1)*. Oct 1996:1-88.

Cumming RB, Cameron BA, Derrick B, et al. "A Comparative Analysis of Claims-Based Methods of Health Risk Assessment for Commercial Populations". *Research study sponsored by Society of Actuaries*. 2002.

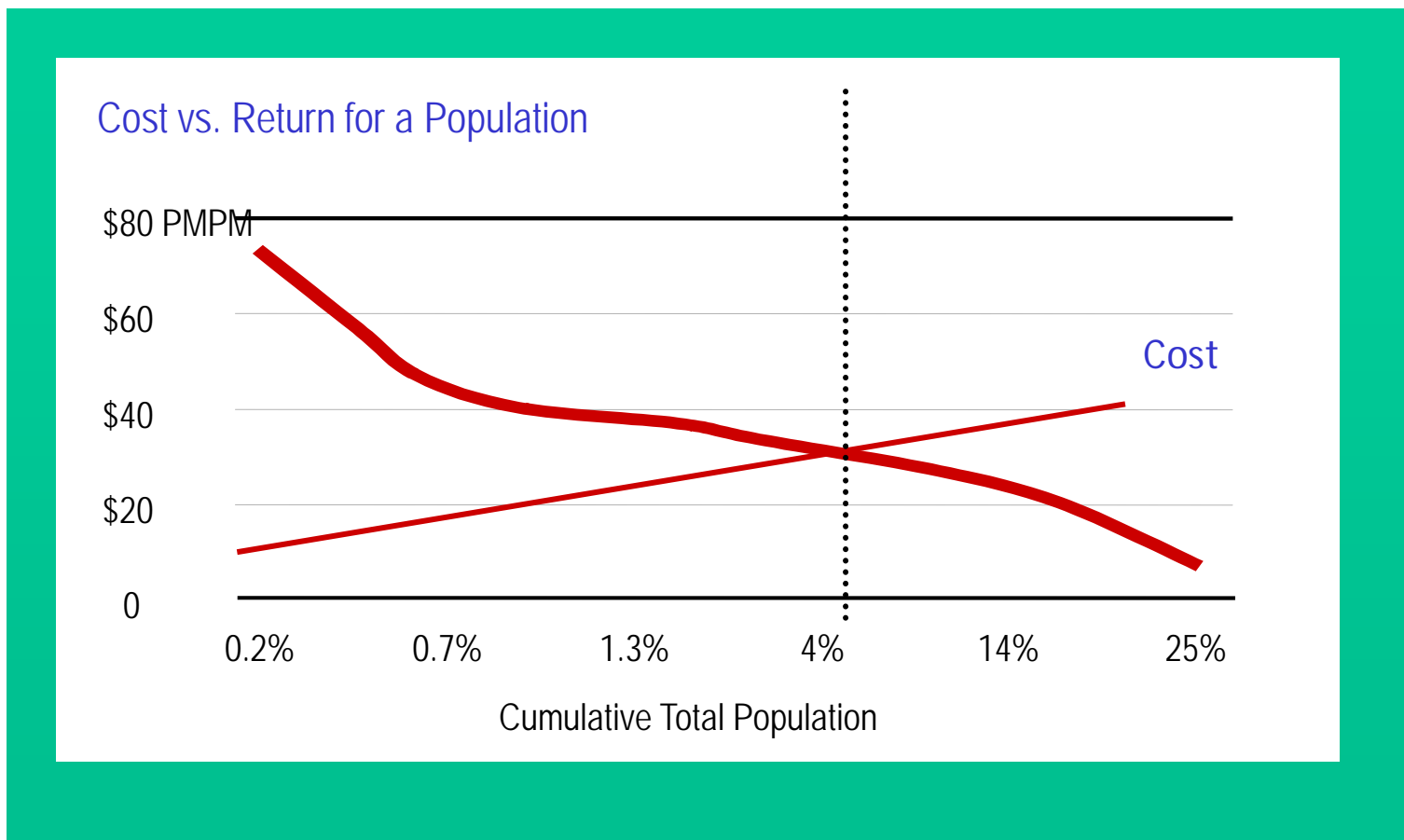
Winkelman R, Mehmud S. "A Comparative Analysis of Claims-Based Tools for Health Risk Assessment". *Society of Actuaries*. 2007 Apr:1-63.
(available at: www.soa.org/files/pdf/risk-assessmentc.pdf).

Commercial Groupers: SOA studies

The Society of Actuaries studies show:

1. Risk grouper modeling tools use *different algorithms* to group the source data. For example, the Symmetry models are built on episodes of care, DRGs are built on hospital episodes, while other models are built on diagnoses.
2. Similar performance among all leading risk groupers.
3. Accuracy of prediction has increased since the publication of the original study. In part, this is due to more accurate coding and the inclusion of more claims codes.
4. Risk groupers use *relatively limited data* sources (e.g. DCG and Rx Groups use ICD-9 and NDC codes but not lab results or HRA information).
5. Accuracy of retrospective (concurrent) models is now in the 30%-40% R^2 range. Prospective model accuracy is in the range of 20% to 25%.

Fundamental Principles of Health Economics



Typical DM Program Economics

A typical telephonic DM program:

Population	1,000	Reachable	70%
Prevalence	6%	Reached	11
Chronic	60	Enrollment rate	70%
High Risk %	25%	Enrolled	7
High Risk Chronics	15		

For this DM program, an employer could pay \$30,000 to \$60,000 annually, or \$100 to \$300 per enrolled member per month.

Evaluation Methodologies

<u>Method</u>	<u>Issues</u>
1. DMAA	Requires trend estimate.
1. Risk factor reduction	Requires risk factors at different time periods and estimate of value for each risk.
3. “Mercer” method	Participant vs. Non-participant method. Normalized for age/sex/risk. “Difference in differences” between par and non-par groups from Baseline.
4. Matched cohorts	Matching on different factors, including propensity and risk factor matching.

Evaluation Methods - DMAA

The prevalent industry methodology is a trend-adjusted historical control methodology.

Simple example:

Estimated Savings due to reduced pmpy =	
Baseline Cost pmpy * Cost Trend	\$6,000 * 1.12 = \$6,720
Minus: Actual Cost pmpy	<u>\$6,300</u>
Equals: Reduced Cost pmpy	\$420
Multiplied by: Actual member years in	
Measurement Period	<u>20,000</u>
Equals: Estimated Savings	\$8,400,000

Evaluation Methods - Risk Factor Reduction

Application to Wellness Programs

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Savings Estimation Based on Female HRA only model

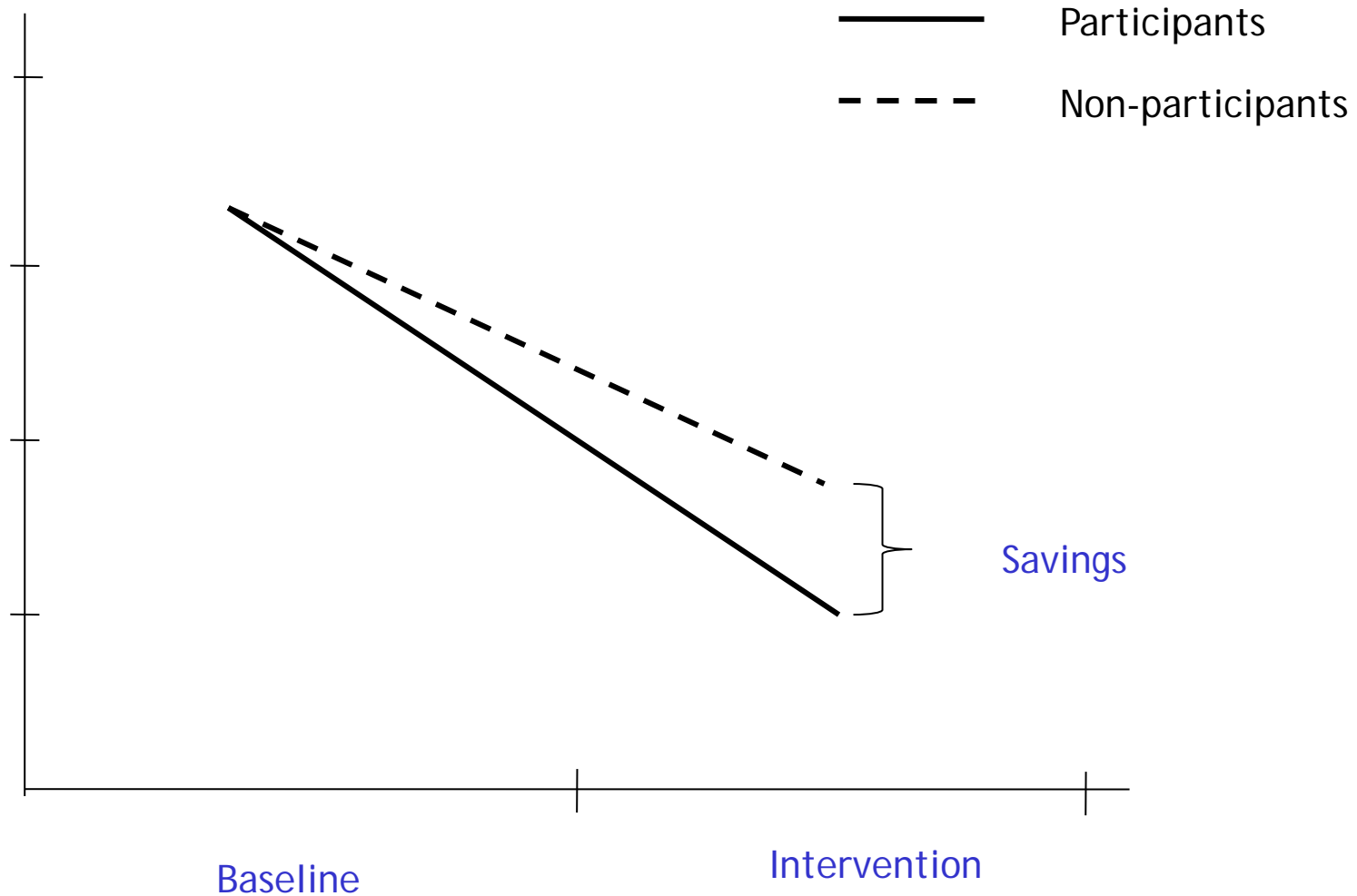
Attribute (a)	Variable (b)	Cost Coefficient (Table 8) (c)	Mean Variable (Baseline) (Table 8) (d)	Mean Variable (Post Intervention) (e)	Cost (Baseline) (f)	Cost Improvement (g)
Weight Management	Body Mass Index	\$118	29.61	28.00	\$349,521	\$(18,981)
Physical Activity	Moderate-intensity physical activity - minutes per day	(46)	13.49	15.00	(61,736)	(6,905)
Stress and Well-Being	In the last month, how often have you been angered?	1,632	0.05	0.04	8,700	(2,196)
Physical Activity	High intensity activities? (hours per week)	(306)	0.34	0.50	(10,450)	(4,835)
Nutrition	Servings of grain per day?	(868)	0.99	1.00	(85,937)	(1,220)
Tobacco	Rate confidence to avoid smoking when blue	(294)	1.74	1.74	(51,089)	(120)
All other variables (in table 8)					263,812	-
TOTAL					\$412,821	\$(34,256)

Evaluation Methods - Risk Factor Reduction

Combination of Clinical Improvement/Literature review for small employer populations

Attainment of clinical indicator	Diabetic complication impacted	Direct Cost savings for mitigated complication
A1C level	Ketoacidosis	\$480.05
	Diabetic Neuropathy	\$3,236.05
	Infections	\$1,348.44
A1C Level and BP	Diabetic Retinopathy	\$4,136.80
	Diabetic Nephropathy	\$863.00
A1C Level, BP, and Cholesterol	Stroke	\$48.54
	CAD (CHF)	\$1,941.67

Evaluation Methods - Mercer Method



Solucia Developments

Enhanced Trend Projection Method

- Addresses an issue in the DMAA method – absence of credible external trend estimate.
- Estimate utilization and unit cost trends separately.
- Example: Medicare utilization trends.

MEDICARE DISCHARGES PER 1000 BY CONDITION*

Year	Diabetes DRG 294	Renal Failure 316	Bronchitis & Asthma 096	COPD 088	Heart 132-144	Syncope 141-142
1998	2.214	2.455	1.597	10.254	17.954	3.283
1999	2.187	2.566	1.773	10.617	17.738	3.367
2000	2.280	2.768	1.470	9.925	18.744	3.608
2001	2.458	3.001	1.352	10.047	19.949	3.915
2002	2.516	3.174	1.428	10.275	19.682	4.089
2003	2.450	3.984	1.385	10.335	18.706	4.259

Annualized

Trend	2.1%	10.2%	-2.8%	0.2%	0.8%	5.3%
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* Actuarial Trend, i.e. per member per month

Solucia Developments

Trend Projection methods – example calculation

MDC #	MDC	1999 Discharges Per 1000	2003 Discharges Per 1000	Annual Increase	Admit Weights	Weighted Trends
01	Infectious & Parasitic	9.8	9.9	0.4%	3.0	0.0
02	Neoplasms	20.6	18.6	-2.5%	0.0	0.0
03	Endocrine etc.	15.7	15.9	0.3%	0.0	0.0
04	Blood Forming Organs	3.8	4.4	3.7%	5.0	0.0
05	Mental Disorders	15.2	15.0	-0.4%	9.0	(0.0)
06	Nervous System	5.1	5.4	1.4%	9.0	0.0

TOTAL		354.2	351.4	-0.2%	27.0	1.0%

Risk factor values

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Savings Estimation Based on Female HRA only model

Attribute (a)	Variable (b)	Cost Coefficient (Table 8) (c)	Mean Variable (Baseline) (Table 8) (d)	Mean Variable (Post Intervention) (e)	Cost (Baseline) (f)	Cost Improvement (g)
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Physical Activity	High intensity activities? (hours per week)	(306)	0.34	0.50	(10,450)	(4,835)
Nutrition	Servings of grain per day?	(868)	0.99	1.00	(85,937)	(1,220)
Tobacco	Rate confidence to avoid smoking when blue	(294)	1.74	1.74	(51,089)	(120)
All other variables (in table 8)					263,812	-
TOTAL					\$412,821	\$(34,256)

Discussion

Thank you for your participation

For more information:

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