Healthcare Risk Adjustment and Predictive Modeling

Second Edition

Ian Duncan, FSA FIA FCIA FCA CSPA MAAA

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FOREWORD to the Second Edition

Jeremy J. Brown, FSA, MAAA
Past-President, Society of Actuaries

It's an exciting time to be a data scientist.

As I look back over the course of my career—nearly 40 years working as an actuary—I'm reminded of how we met the emerging challenges of actuarial science as they came. As the risks changed, we evolved and innovated, whether we were designing products and strategies in years of rising interest rates, rising equity markets or historically low interest rates.

I spent just as much time as a volunteer educator, working to advance actuarial science as a field and the profession as a whole, and teaching the next generation of actuaries the skills they need to do the same.

However, I haven't seen anything with as much potential to revolutionize the healthcare field as the advent of predictive analytics. Working in healthcare analytics is all about making assumptions and testing it with data. When I started out, I never imagined how easy it would become to transform massive data sets into predictive patterns and models. This book makes it even easier, laying out the analytical techniques that underlie the models and then showing them at work through case studies that take the theory into real-world applications.

Big Data is nearly everywhere, and we are collecting data on nearly everything. Tech companies are in the cultural spotlight, dominating the headlines and accumulating vast data reserves. Yet the skills needed to analyze that data, and, more importantly, to create a predictive model capable of making use of that data, aren't really the purview of the tech firms that collect them.

Creating models, making assumptions, and testing them is our purview. Using models to predict and mitigate business risk is our bread and butter, and that's why it's such an exciting time to be an actuary.

There isn't a single profession better suited to meeting this emerging industry need. We have the skills to make use of predictive analytics, and most importantly, we have the future-tense mindset that drives us to think about what data is telling us, what will happen, and how to plan for it. We do not simply analyze what has already happened. Work like Ian Duncan's is essential to help educators and those working in healthcare analytics apply the latest advances in data science to the real challenges in the field.

Actuaries have always trained to make use of the things predictive analytics can uncover. Now, we're changing our curriculum to encompass books like this one, which teaches us how to harness predictive analytics itself. I am optimistic that this book will contribute to the interdisciplinary collaboration necessary to find solutions to today's healthcare challenges.

Jeremy Brown retired from Mutual of America Life Insurance Company where he served as Executive Vice President and Chief Actuary. He is a past president of the Society of Actuaries.

FOREWORD to the First Edition

Regina Herzlinger
Professor of Business Administration
Harvard Business School

What percentage of healthy people will become catastrophically ill one year later? And what percentage of the chronically or catastrophically ill will become healthy a year later?

Hint: The right answer is not zero.

Give up? The answer is in Ian Duncan's analysis—a surprisingly high 20% and 15% respectively. *Healthcare Risk Adjustment and Predictive Modeling* is full of interesting statistics like these. But this book contains much more than that.

As healthcare payers increasingly require providers to accept pay for performance or bundled payments for episodes of care, disease or disability focused bundles, or even global care, it is important to separate payments for things providers can control (their medical management) from those they cannot (the underlying health status of the enrollees and acts of God). The ability to differentiate payment for *performance* from payment for *health risk* is important for health care policy makers, related academics, and think tanks as well.

Ian Duncan had previously literally written THE book on the evaluation of intervention programs (you see it on the bookshelf of every disease manager for example). And now as bundled payments and P4P loom, he has performed the same valuable service for health risk analysis.

The analytical techniques Duncan discusses range from the readily approachable, requiring no more than basic algebra and calculus knowledge—various grouping methodologies, statistical regression analytics, parsing decision trees—to artificial neural networks (don't ask). But to be useful this kind of book must be a blend of mathematics and pragmatism. Have no fear. A series of concluding chapters provides helpful case studies on how to use health risk analysis for designing programs in health care reform initiatives (such as the "Connector," the Massachusetts version of an Exchange) and evaluating provider efficiency, with vivid examples drawn from both U.S. and Europe.

All in all, this is the work of another brilliant yet practical mind:

—A brilliant exposition of analytical techniques, coupled with
—A masterful explanation of how to apply health risk analysis in a series of relevant, real world case studies.

Regina E. Herzlinger is the Nancy R. McPherson Professor of Business Administration at the Harvard Business School. She was the first woman to be tenured and chaired at Harvard Business School and the first to serve on a number of corporate boards. She is widely recognized for her innovative research in health care, including her early predictions of the unraveling of managed care and the rise of consumer-driven health care, a term that she coined. *Money* has dubbed her the "Godmother" of consumer-driven health care.

PREFACE

This book resulted some years ago from a brief conversation with Nancy Turnbull of the Harvard School of Public Health, my colleague at the time on the Board of the Massachusetts Health Insurance Connector Authority, and Associate Dean of the Harvard School of Public Health. Risk Adjustment of payments to health plans was a topic discussed by the board from time to time, and Nancy suggested that, as the momentum for national health reform built in 2008-9, a text on predictive modeling and risk adjustment would provide a timely and useful contribution to the practical implementation of reform. I had conducted seminars for the Society of Actuaries on healthcare predictive modeling and risk adjustment for a number of years, so the basic material existed. As with my previous book, *Managing and Evaluating Healthcare Intervention Programs* (ACTEX Publications, 2nd edition, 2014), the rounding out of the basic material required contributions from a number of individuals. I would like to recognize and thank those individuals who have made contributions to the writing or review of early drafts of both editions this book.

Second Edition

I had considerable assistance with this edition from students of the Department of Statistics & Applied Probability at the University of California, Santa Barbara. These included Jason Goellnitz, BS, and Emily Zhang, MS. Dominic Mullen, MS, provided valuable assistance both in modeling and in editing the manuscript. My Research Assistant, Nhan Huynh, MS, contributed enormously to many chapters. Several individuals have also contributed to different chapters:

Appendix 3.9: Blaise Guzewicz, General Counsel, SCIO Health Analytics.
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Chapter 22: Andrew Webster, ASA, MAAA, Validate Health.
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Laurie Weissbrot.
Finally, my new editor, Stephen Camilli, FSA, President of Actex Learning, provided considerable input and the occasional nudge!

First Edition
A number of co-authors and research assistants have contributed to different chapters. Primary among these is my colleague Qijuan (Emily) Li, MPH of Solucia Consulting, who has performed data analysis and constructed the examples in this book using Solucia's extensive health claims databases. Other Solucia colleagues who have made contributions are Tamim Ahmed, PhD, MBA; Christian Birkmeyer, MS; Mark Howland, ASA, MAAA; Arthur Robb, PhD; Lisa Tomei, MS; and Greger Vigen, FSA, MBA. Outside of Solucia Consulting, contributors to chapters are Professors Xiaogang Su, PhD, School of Nursing of the University of Alabama at Birmingham and Wu-Chyuan Gau, PhD, ASA, Department of Mathematics and Actuarial Science, Robert Morris University, to whom I am indebted for the statistical chapters (Chapters 7 through 12). I am also grateful to my able TA at the UCSB Department of Statistics and Applied Probability, Nate Bennett, PhD, for proofreading the statistical chapters.

Others who have contributed to different chapters are:

Chapter 6: Development of DRGs: Henry Dove, PhD, MBA, Yale University.
Chapter 13: Medicaid Risk Adjusters: Ross Winkelman, FSA, MAAA, Wakely Consulting.
Chapter 14: Medicare Advantage and HCCs: Jim Galasso, FSA, MAAA, CERA, Actuarial Modeling.

Chapter 15: Health Care Reform—the Example of Massachusetts: Jonathan Gruber PhD, Professor of Economics, Massachusetts Institute of Technology and board member, Massachusetts Health Insurance Connector Authority.

Chapter 20: Predictive Modeling and Risk adjustment in the UK and Europe: Geraint Lewis, MB, ChB, and Martin Bardsley, PhD, of the Nuffield Trust, London contributed to the section on the United Kingdom. Other parts of this chapter are taken from material published in *Contingencies*, the periodical of the American Academy of Actuaries and are used with permission of the Academy. The Section on Israel was contributed by Yair Babad, PhD, Emeritus Professor of the University of Illinois at Chicago, and the Section on Risk Adjustment in South Africa contains contributions from Barry Childs FIA, and Francois Millard FSA, FIA, MAAA.

As with other actuarial texts, the active participation of a number of reviewers was also valuable. I must thank the reviewers for this book for their time and helpful comments.

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As always, great credit for setting and reviewing the text go to my publisher and editor, Gail Hall, FSA, MAAA, and format editor, Marilyn Baleshiski of ACTEX Publications. I am also grateful to my able TA and the UCSB Department of Statistics and Applied Probability, Nate Bennet, PhD, for proof-reading the statistical chapters.

And last but not least, this book is dedicated to my wife, Janet Duncan, FCAS, FSA, MAAA, who has (again) had to spend weekends alone while I worked on another book about health insurance. But at least this time she could do it in Santa Barbara!

Ian Duncan, FSA, FIA, FCIA, FCA, CSPA, MAAA, Santa Barbara, CA
April 2018

INTRODUCTION

David B. Nash, MD, MBA

The *Economist* magazine calls it, "the inexorable logic of the data economy".[1] That is, the broadening recognition that large datasets contain information about human health that may become invaluable. As societies spend more money on healthcare, payers are desperate for insights that "might enable them to cut costs while maintaining quality. The more data the tech firms can handle, the more they will learn about human health and the better the services they can offer can become."[1]

I certainly embrace this inexorable logic, and therefore was so excited to read the second edition of Ian Duncan's successful book, *Healthcare Risk Adjustment and Predictive Modeling*. No longer an arcane science, practiced by "green shades" in the back office, modeling is now solidly mainstream. Since it became mainstream, we need a guidebook, a how-to, pragmatic, step-by-step assessment that will help us to extract the information from the tsunami of data that threatens to drown us all. Duncan delivers!

This is particularly relevant in an era when many Americans cannot define the basic components of health insurance, like a copayment, or discern the difference between copayment and co-insurance. As payers in the United States recognize that the road from "volume to value" is paved by bearing economic risk, I have developed a diagnostic litmus test question that I pose to most leaders of provider-based organizations. My question is, "how many actuaries do you employ?" Frankly, many times highly educated leaders in healthcare ask me, "what exactly is an actuary, and what do they do?"

When one couples the paltry understanding of the basic tenets of health insurance, along with a lack of appreciation for the work of healthcare actuaries, it puts the system at risk. Once again, enter Ian Duncan and the clarity of his prose.

As I delved deeper into the book, my favorite section emerged—namely section three, where Duncan describes model application with pragmatic examples, many of which make sense in my day-to-day work as an educator, policy maker, and thought leader in the world of population health.

If you accept the notion that nearly 60% of Medicare revenue will be tied to risk in the next few years,[2] then our ability to assess this risk becomes paramount. Again, Chapters 15 and 16 within Section 3, helped to address this paramount need.

Risk adjustment and predictive modeling are not the same as artificial intelligence or machine learning,[3] but I'm confident that we cannot make progress without a deeper understanding of risk adjustment and modeling in many different sectors. Duncan has given us a roadmap that connects these seemingly disparate worlds of risks and AI.

Who should read this book? Well, it's not bedtime reading for the average practitioner, but it surely is mandatory reading for leaders and aspiring leaders of the largest industry in the

United States. Careful observers of the healthcare ecosystem in our nation know that current spending is not sustainable, and we're going to have to make some difficult decisions. I hope that senior decision makers embrace Duncan's work and utilize his tools to allocate scarce resources in a way that moves us further on the road from "volume to value."

I admonish our students in the nation's first College of Population Health to "shut the faucet" rather than "mop up the floor." Duncan has given us elegant tools to figure out exactly which faucet we are to shut, how long to keep it shut, and which faucets to avoid altogether! Kudos to Duncan for his contribution to the conversation surrounding the healthcare system. I hope that our leaders are willing to look in the mirror, self-evaluate, recognize their shortcomings, and pick up this book and read it now!

David B. Nash was named the Founding Dean of the Jefferson College of Population Health (JCPH) in 2008. He is also the Dr. Raymond C. and Doris N. Grandon Professor of Health Policy. JCPH provides innovative educational programming designed to develop healthcare leaders for the future. Dr. Nash is a board-certified internist who is internationally recognized for his work in public accountability for outcomes, physician leadership development, and quality-of-care improvement. Dr. Nash received his MD from the University of Rochester School of Medicine and Dentistry and his MBA in Health Administration (with honors) from the Wharton School at the University of Pennsylvania.

References

1. Anonymous. Digital health – surgical intervention. *The Economist*. February 3, 2018, p. 53-55.
2. Leventhal R. Survey: By 2019, 60% of Medicare revenues will be tied to risk. *Healthcare Informatics*. December 12, 2017. www.healthcare-informatics.com
3. Davenport TH, Ronanki R. Artificial intelligence for the real world. *Harvard Business Review*. January-February 2018, p. 109-116.

ACCESS TO DATA SETS AND R CODE

As part of your purchase of this book, you should have received a key to access four test data sets mentioned in this book. If you have any issues accessing these data sets, please contact the publisher at support@actexmadriver.com. The R code included in appendices to chapters is included in the supplements section of the publisher's website, www.actexmadriver.com.

SECTION ONE

INTRODUCTION AND BACKGROUND

1 INTRODUCTION TO HEALTH RISK

1.1 WHAT IS HEALTH RISK?

This chapter covers the basic concepts that any actuary or analyst should understand before tackling risk adjustment or risk prediction: what exactly *is* health risk? For something that surrounds us on a daily basis, the term is difficult to define, and can have many different meanings, depending on context and who is doing the defining. It has a number of synonyms as well, such as case mix, severity, intensity, and health status. Another term that has become current recently is identification and stratification, or "ID & Strat" as it is usually called, a useful term because it focuses not only on relative risk ("strat") but also on the population at risk ("ID"). We will cover the specific definitions of some of these terms later. For now, we concentrate on "health risk."

At its most fundamental, risk is a combination of two factors: **amount of loss** and **probability of occurrence**. For the purpose of this book, we define a loss as having occurred when an individual's post-occurrence state is less favorable than the pre-occurrence state. Financial risk is a function of loss amount and probability of occurrence, but in healthcare, risk and loss are not restricted to financial quantities only. We therefore use the following, more general, definition:

Risk ~ *F*(Loss, Probability)

In healthcare, we are interested in many different states. Actuaries are most frequently interested in financial loss, which occurs because an event, which occurs when there is a change in state[1], imposes a cost on an individual (or employer or other interested party). To a clinician, however, a loss could consist of a loss of function, such as deterioration in an organ or an inability to perform at a previous level of functionality.

Actuaries are the leading professionals in the identification, measurement and management of risk. The measurement of risk requires the quantification of losses and the estimation of the probability of their occurrence. Management of risk requires the identification of ways in which either the amount of losses or the probability of their occurrence (or both) may be mitigated. While actuaries are primarily interested in financial risk, the types of risk prediction models discussed in this book may be applied to many different states and types of losses.

[1] Modern actuarial theory encompasses Markov-type analysis of changes in state. See, for example, Chapter 8 of the recommended Society of Actuaries and Institute and Faculty of Actuaries textbook for the life contingencies examination. Dickson Hardy and Waters (2013) [1].

Some risks may be assessed simply—the loss resulting from being hit by an automobile while crossing a street is rather high and encompasses medical expenses, loss of future function and loss of income; the probability of such an event occurring is, however, slight. In addition, the risk may be mitigated almost entirely by crossing at a designated intersection and obeying the crossing signal.

Health risk is a more complicated concept because it exists on many levels in many contexts. We now discuss some common types of health risk encountered by the actuary. In the next section we will cover two frequently-confused concepts, pricing risk and underwriting risk, as well as some of the risk factors that contribute to individual risk, and the relationship between individual and population risk. Finally, because in health insurance, actuaries often work with clinicians, we will briefly cover some of the differences between a *financial* (or actuarial) view of risk and a *clinical* view.

1. The most obvious health risk confronted by actuaries is **pricing risk**. An insured health plan accepts pricing risk by agreeing to reimburse unlimited health-related services (limited only by medical necessity and any other restrictions defined in the insurance contract) in exchange for a fixed monthly premium.[2] This pricing risk can take one (or both) of two forms that coincide with the two risk concepts defined earlier—loss and probability. A health insurer's actual experience can be equal to the expected *number* of claims, but at the same time include more large claims. Alternatively, individual claims may be of modest size, but the company could simply experience a higher-than-expected *volume* of them. Risk that we have defined as comprising loss and probability is also often defined in terms of severity (size of claim) and frequency (number of claims).

    a. **Severity**: the amount of a loss in healthcare must be estimated because health policies (with some exceptions) do not specify the amount that is to be paid for a specific service, or even what bundle of services is considered medically necessary to treat a particular condition. Health insurance policies generally agree to pay for those services ordered by the physician that are deemed medically necessary (by the insurer) for the patient's condition. Exclusions of services are rare in health insurance policies, although they are not unknown (for example, prior to the Affordable Care Act, a policy might not cover prescription drugs, or could exclude certain imaging services). Another category of exclusions that gives rise to difficult discussions is services that are considered to be "experimental." More frequently, services are covered with cost-sharing or limits on frequency (for example limits on the number of chiropractor visits, or prior to the Mental Health Parity act of 1996 and its successors, the number of visits to a mental health provider), or are subject to pre-authorization. Individuals experience medical conditions in different ways, and medical practitioners are free to treat patients differently and to try new (and often more expensive) treatments. As the work of Jack Wennberg, MD, and others associated with the Dartmouth Atlas of Healthcare (available at www.dartmouthatlas.org) has shown, providers often treat the same condition in different ways, leading to the well-known concept of **Geographic**

[2] Many employer-sponsored health plans are ASO, or Administrative Services Only. In this type of plan, the employer retains the financial risk. The third-party administrator (that could be an insurer but may not be) undertakes the administrative risk only, often at a fixed price, but the employer retains the financial (claims) risk. Actuaries acting as benefits consultants to employer groups assume a role similar to that of health plan actuaries in advising employers on pricing and management of the employer's risk.

Variation in practice patterns. Different contractual arrangements between providers and payers even result in the same procedures and treatments being reimbursed at different amounts. This combination of factors results in unpredictable losses, even for a given set of clinical circumstances.

b. **Frequency**: in setting pricing for a health insurance product the actuary assumes certain probabilities or frequencies of different types of claims. The frequency of claims may, however, be influenced by several types of endogenous (internal) and exogenous (external) factors:
    i. patient factors: the insureds themselves, their conditions, and their adherence to the advice of their medical providers;
    ii. provider factors such as the training that the providers have received and the evidence-based medicine standards that are practiced;
    iii. exogenous factors such as the development of new technology, lack of access to previously available services, or publicity and advertising of new services; and
    iv. factors designed to encourage certain types of behavior on the part of both patients and providers. Traditionally, patient behavior has been managed through plan design (co-pays, deductibles, etc.), although more recently, numerous intervention programs have been developed for this purpose. Provider behavior has been managed through networks, pre-authorization and now, pay-for-performance and value-based contracting.

2. Closely linked to, but not identical to, pricing risk is **underwriting risk**.[3] In setting a price for an insurance product, the actuary is expecting that the overall risk pool will perform, on average, at the estimated total claim level. Some participants in the pool will cost more and others less than the projected average. Sound financial management of an insurance pool requires underwriting standards to be set at such a level that the actual distribution of member risks in the pool approximates the distribution of members expected in the pricing. Too many high-risk members or too few low-risk members will result in the overall claims exceeding those expected in pricing. Controls on access could include a requirement that the potential member demonstrate good health at the time of application, be subject to exclusion of claims for pre-existing conditions, be subject to a limitation on high-cost procedures, or be required to seek care from a network of physicians who are known to practice conservatively or efficiently. The underwriting process should identify members with risk factors such as a high-cost condition, family history of certain illnesses, or potentially risky lifestyles (such as smoking). It is important to note, however, that even when health underwriting is applied, the underwriting process is not symmetrical—the individual applicant for insurance *always* knows more about his or her health status than the underwriter. The management of large claims may include reinsurance of high amounts and care management programs targeting certain high-risk conditions. The Affordable Care Act[4] (ACA) prohibits underwriting, exclusion of pre-existing conditions

[3] This discussion is theoretical, in light of the prohibition on underwriting and exclusion of pre-existing conditions contained in the Affordable Care Act (ACA). Nevertheless, we discuss underwriting as part of the health actuarial "tool-kit." The ACA replaced underwriting with other risk management techniques, which we shall discuss later. The American Healthcare Act which was discussed in Congress in 2017 but failed to pass would have allowed for the reintroduction of limited underwriting in some circumstances.

[4] The Patient Protection and Affordable Care Act (PPACA) commonly called the Affordable Care Act (ACA) or Obamacare, Public Law 111–148—March 23, 2010.

or variations in pricing by age other than within a relatively narrow band (3:1 differential between highest and lowest rates).[5]

We may loosely distinguish between underwriting risk and pricing risk by thinking of the former as resulting from the cost of unknown risks while the latter is more related to the cost of known risks. Said another way, pricing risk occurs when setting the price for a book of business or population; underwriting risk occurs when agreeing to accept a new entrant to a population, and is affected by the rate and terms at which that entrant is accepted.

3. The ACA prohibits the application of underwriting, so the insurer cannot exclude or rate-up members that are likely to be high claimants with, for example, a pre-existing condition. Nor can an insurer exclude claims for a pre-existing condition. Instead, the onus is on the insurer to manage, as well as possible, the high claims. There are many techniques for doing this (see, for example, Duncan (2014) [2]) which frequently involve identifying future high-risk members so that their care can be managed. If, as we have discussed, potentially high-claiming individuals drive underwriting risk, what risk factors imply that an individual may potentially generate high claims? We can, for the purpose of this discussion, categorize factors as follows:

    a. Inherent risk factors such as age, sex, or race. These are factors that are immutable, as compared (for example) to geographic risk, over which the individual has some control. Some readers may find it difficult to accept these characteristics as "risk factors." Objectively, however, they are associated with differential risk levels (losses and probabilities of losses). Actuaries can and do assess these differential risks; it is for the market and the regulators to determine (as they do) which risk factors may be applied in practice to price or underwrite products. Actuaries have for many years used age and sex as predictors of a population's risk and expected claims. As the Society of Actuaries studies have shown[6] these factors are associated with future claims. Including prior claims levels in the list of risk factors increases the correlation.

    b. Medical condition-related risk factors such as diabetes or cancer. Individuals with these types of conditions will clearly generate higher claims than members who do not have serious medical conditions.

    c. Family history. Some risk factors and medical conditions, such as hemophilia or certain cancers are inheritable. Information about family history can therefore be helpful to the pricing, underwriting and management of health risk. Predisposition to disease may be identified through genetic testing, something that has grown significantly in recent years with a number of companies offering to provide genetic information for an affordable price. Nevertheless, the use of such genetic information for pricing and underwriting is prohibited in most jurisdictions,

[5] The previously proposed American Healthcare Act would have restored pricing variation by age to something more closely resembling the underlying cost factors. This law failed to pass. At the time of writing there are movements in individual states to restore some elements of underwriting.

[6] Society of Actuaries risk adjuster studies, for example Rosenblatt et al. 1996 [3]; Cumming et al. 2002; [4]; Winkelman and Mehmud 2007 [5]; G. Hileman and S. Steele, 2016 [6].

increasing the asymmetry of information between insurer and insured. "Most states have outlawed discrimination in employment and health insurance based on predictive genetic information" (Ashley, [7], 2005).

d. Lifestyle-related risk factors, such as smoking, stress, seatbelt use, lack of exercise, and poor nutrition contribute to higher cost. Some of these factors will have a short-term impact on member cost; other factors, such as obesity or smoking, will take years to have an effect on member health, leading to the emergence of medical conditions later.

e. Exogenous risk factors. These include: the industry in which an individual works, the location of his home, his education level, and cultural or religious beliefs.

4. **Population versus individual risk**. The risk of a population will be different than that of an individual, because of the "spread of risks" that is inherent when a number of lives are pooled in a population. An individual may be highly risky because of his condition-based risk or lifestyle risk factors, yet the population of which he is part may not represent a significant risk. Conversely, in a small population, a single catastrophic event could result in a large loss to the population or group. Furthermore, it is not only catastrophic events that represent significant population risk—a relatively small increase in the frequency or cost of some basic services delivered to the larger population can result in the overall losses in the population being much larger than anticipated by the pricing. Even if individuals represent a predictable and unchanging condition risk, a change in the mix of individuals (e.g. more individuals with heart disease and fewer with asthma) can represent a significant increase in hospital utilization and cost. Population risk is not only a function of large claims amounts or higher frequency of claims. The behavior of low-claiming members of the population, whose participation is required to support the cost of the population, also affects the experience of the pool, which could be adversely affected if the participation of low-claiming members does not materialize, as has arguably been the case with the ACA.

5. **Event Risk versus Financial Risk**. Actuaries tend to think in terms of financial risk, and indeed it may seem unnecessary to separate out event and financial risk, since events (or "**occurrences**") ultimately are translated into financial loss. Clinicians, however, tend to think in terms of events (admissions to the hospital; visits to an outpatient facility; loss of physical or mental function) rather than financial losses, so we should recognize that risk may mean different things to different audiences.

All of these risks have a place in the concerns of those managing an insurance company or an insurance pool. At its heart, health risk is a combination of the amount and probability of a loss. Management of an insurer's risk requires that the actuary be able to predict as accurately as possible both the frequency and the severity of claims, and the development of techniques to manage both of these factors. As we explore in this book, predictive modeling is one technique that helps actuaries more accurately predict both frequency *and* severity of claims.

We will cover risk prediction and risk adjustment based on lifestyle factors later in this book. Risk adjustment is related to risk prediction, and the two terms are often used interchangeably. We address the difference in Section 1.3, where we will attempt to differentiate between the two, showing their similarities and differences. Later in the book,

in case studies, we will show where each is applicable in healthcare risk management. First we will cover the more traditional area of actuarial concern—**medical condition-based risk**.

1.2 HEALTH RISK MANAGEMENT

Most health insurers have traditionally managed risk by a combination of pricing, underwriting, and reinsurance, together with claims management. At least since the HMO Act of 1973 (42 U.S.C. § 300e), **Managed Care** developed as a series of initiatives designed to reduce claims costs. The original approaches included **network contracting** (identifying and contracting with preferred providers who offered either lower rates or lower utilization of services and steering patients to them, either through benefit design or by requiring referrals) and **utilization management** (pre-authorization or concurrent review of hospital admissions). Because of consumer reaction to the denials that resulted from pre-authorization, managed care plans began to seek other solutions to contain rapidly increasing costs. Techniques that are favored for managing utilization include the implementation of programs that encourage members to take responsibility for their own health, or that aim to educate physicians in the most cost-effective, evidence-based treatments. As the discussion above showed, underwriting and the exclusion of pre-existing conditions were important risk management techniques and are now outlawed in the market for insured policies. The inability to use these traditional methods will increase the importance of care management techniques in the future.

Care Management programs and interventions target different actors and different areas of utilization. One way of examining intervention programs is to identify the target of the intervention, as in the following table.

TABLE 1.1

Types of Medical Management Interventions		
Care Coordination *Focus on the System*	**Condition Management** *Focus on the Patient*	**Provider Management** *Focus on the Provider*
▪ Care coordination (between providers) ▪ Intensive case management ▪ Behavioral health case management ▪ Discharge planning ▪ In-hospital care coordination ▪ Concurrent review ▪ Clinical best practices and treatment guidelines ▪ Bundling of services	▪ Chronic condition (disease) management ▪ Case management ▪ Maternity management ▪ Behavioral condition management ▪ Wellness and risk factor management ▪ Specific condition management e.g., diabetes, HIV ▪ Centers of excellence	▪ Concurrent review ▪ Prescription drug management ▪ Network development, provider profiling, up-coding, unbundling and fraud identification ▪ Prior authorization ▪ Pay-for-Performance ▪ Medical homes ▪ Bundling of services ▪ Centers of excellence ▪ Accountable Care Organizations

Unlike **pre-authorization,** which is largely implemented through a series of rules and administered at the claims level by the insurance provider, management programs (either case management or disease management) are human resource-intensive. Because staffing requires individuals with clinical skills and experience to manage each case individually, these programs are costly to implement and manage. Successful programs that demonstrate return on investment require that only the right, potentially highest-opportunity members be identified for intervention. Because it is difficult to identify "high opportunity" members, interventions most often default to highest-risk members. An example of the use of predictive modeling in the planning of such a program is discussed in Chapter 16.

1.2.1 WHAT IS A HIGH-RISK MEMBER?[7]

High risk members, in our definition, are members who are expected to have either a high loss amount, or a high probability of a loss occurring, or both. Traditional risk-management methods do not distinguish between high cost and high risk members. With other insurance coverages (e.g., fire, workers' compensation), the identification of potential risk factors is an essential component of programs of risk management or risk reduction. The same techniques have been slower to penetrate health insurance, until recently, because it is more difficult for the insurer to intervene in something as personal as an individual's health.

Health plan professionals have different ideas of what constitutes a high-risk member. A health plan's underwriting process may identify members for high-risk management that have risk markers for certain diseases (such as cancer or heart disease) because of a family history. Other health plan administrative processes may also identify risks within the population. While such an identification method may be possible for an entire population, there are several problems with this approach.

- There is currently no consistent or successful method (of which we are aware) for obtaining the necessary data on members of a health plan. The information has to be obtained from the member by questionnaire (Health Risk Assessments), from physician and other medical records, often by manual processes, or, as we discuss in later chapters, from claims data. Acquiring data by questionnaire or from physicians is costly, and the response rate to questionnaires is well below 100%, while the data obtained is often inaccurate.

- The data may be of low quality. Even with the best of intentions, members may not respond truthfully to a survey, may not understand the question, or may interpret questions in a way that was not intended. Questions worded slightly differently may solicit a completely different response, and a question may not be asked consistently over time or between different surveys. Moreover, the usefulness of a prediction tool is limited by the generality of the underlying data used to construct the tool. Survey data is notoriously prone to response bias (e.g., the respondent gives the surveyor the response that he or she thinks the surveyor wants to hear).

- While a member may be at risk of adverse health outcomes and report such risk factors in a questionnaire, it is difficult to predict when (or whether) that outcome will occur for any one individual. For many high-risk members, the adverse event may not take place for many years, if at all.

These observations lead us to propose a definition of a **high-risk member** for the purposes of this chapter:

- The member has a significant probability of experiencing costs higher than the average of the group of which he/she is a member, and

- The predicted costs will occur in the near future, such as, the next twelve months.

[7] This section borrows material from Duncan [2].

1.2.1.1 Trends in Health Risk over Time: Why Modeling is Important

Tables 1.2 and 1.3 illustrate some important basic components that are fundamental to understanding predictive modeling and risk adjustment. The tables track the status of members who are *continuously enrolled* in a health plan for the two-year period from Year 1 through Year 2 (specific years are not important—we are illustrating the principle of transition between states). For this analysis, members have been assigned to three **Medical Expense Categories** in the Baseline year (Year 1). The specific categories are somewhat arbitrary, but they may be broadly described as "Healthy" (claims under $2,000 per year), "Chronic" (claims between $2,000 and $25,000 per year) and "Catastrophic" (claims over $25,000 annually). The average cost per member per year (PMPY) in the baseline year (Year 1) is $3,090, which readers may recognize as reasonably consistent with typical national allowed charges for medical plus drug expenses of commercial members enrolled in a health plan in 2007[8]. The Healthy population is $510 in the baseline year; the chronic population cost is about twice the average, or $6,157, and the catastrophic group's cost is considerably higher than the average, at $55,197.

It is important to note that Tables 1.2 and 1.3 track c*ontinuously-enrolled* members. Thus we do not include the usual entry or termination of members (and employer groups) that will influence the average health plan costs of coverage and trends over time. The PMPY trend in allowed charges between Year 1 and Year 2 in our continuously-enrolled population is $3,520/$3,090, or 13.9%, which readers will recognize as being higher than the experience of a typical health plan in which members are entering and leaving. If we included entrants and leavers in the comparison (no continuous eligibility requirement), the trend would be 5.9%, closer to national averages for the period from which the data are drawn. An open group will benefit from new entrants who will often be more healthy (and therefore lower cost) than a pool of mature members, both because they had to meet underwriting requirements (at the period from which the data are drawn), or the "actively-at-work" requirement in employer groups, because employer hiring practices impose a degree of selection. Without the ameliorating effect of younger, healthier lives entering the pool, closed group trends will appear to be higher than those in an open group.

The Chronic and Catastrophic cost groups together constitute about 30% of the total population in the baseline year, but account for nearly 90% of the total cost, an observation commonly referred to as the "80/20 rule"[9] (even when the percentages are not, as in our example, exactly 80/20). In this example, the Healthy cost group amounts to almost 70% of the population but accounts for only 11% of the baseline year cost.

[8] According to a recent 2016 Willis Towers Watson report [8], the average cost of medical benefits per employee per year in 2017 was $12,954 (although on a net paid basis, not allowed charges). Converting to PMPY and assuming an average family size of 2.1 implies a PMPY net paid cost of $6,169. In what follows we will use the 2007 data, although the reader may wish to convert to more current charges by doubling the 2007 numbers.

[9] **The Pareto Principle or the "80/20 rule."** An application of the Pareto principle to healthcare utilization is the frequent observation that a small percentage of any population (often 10% or 20%) accounts for a large percentage of that population's resource utilization, or claims. Often the percentage of the population's resources accounted for by the high-utilizing fraction is the complement of that group's percentage of the total population, hence, the name "80/20 rule."

TABLE 1.2

Member Movement Between Years					
	Membership				
			Year 2 Cost Group		
		Baseline Percentage Membership	LOW <$2,000	MODERATE $2,000 – $24,999	HIGH $25,000+
Baseline (Year 1) Cost Group	LOW <$2,000	69.5%	57.4%	11.7%	0.4%
	MODERATE $2,000-$24,999	28.7%	9.9%	17.7%	1.1%
	HIGH $25,000+	1.8%	0.2%	0.9%	0.6%
	TOTAL	100.0%	67.6%	30.3%	2.2%

The implication of the analysis for predictive modeling may be seen in the transition of members between cost groups. The first point to note is that the overall cost distribution remains relatively stable. Healthy members account for 69.5% of all members in the baseline year and almost 67.6% in the subsequent year. (Remember that we have not adjusted the categories between the two years, even though with trend[10] there is a tendency for the lowest category to shrink and the higher categories to grow over time.) Within the low-cost category (67.6%), however, 85% of members (57.4% of the total 67.6%) were previously healthy, and 15% regressed from Chronic or Catastrophic categories to Healthy. Conversely, Catastrophic cost members were 1.8% of the population in the baseline year and 2.2% in the subsequent year. Fewer than one-third of these members (0.6% of the total 2.2%) were previously Catastrophic.

Fully 20% of catastrophic risk members (0.4% of the total 2.2%) with an average cost of over 100 times their baseline cost ($56,167) were healthy in the baseline year, with an average cost of $510. It is the transition of significant numbers of members from high cost to low cost, and from low cost to high cost that creates the opportunities for predictive modeling and risk adjustment and their applications within healthcare actuarial work. To the extent that there are common, identifiable factors that are associated with the members that transition, these factors may be applied to populations and used to identify, ahead of time, the members who will transition. In a 100,000-member population, 0.4% of members equals 400. With an average subsequent year cost of $56,000, the total claims of these members amount to $22 million in a year. Appropriately rating these members in a renewal will make the difference between a profitable and an unprofitable group. Finding and managing the care of even 10% of the members transitioning from Healthy to Catastrophic could save $2 million, or nearly $2.00 per member per month.

[10] Trend is defined as the relative change in a per capita measure (such as claims costs) year on year. In this case, Trend (Year 2 vs. Year 1) is equal to $\frac{\text{Year 2 cost - Year 1 cost}}{\text{Year 1 cost}}\%$.

TABLE 1.3

Member Cost Movement Between Years					
		Year 1 PMPY[11] CLAIMS	**Year 2 Cost Group PMPY CLAIMS**		
		Mean Per Capita Cost	LOW <$2,000	MODERATE $2,000 – $24,999	HIGH $25,000+
Year 1 Cost Group	LOW <$2,000	$510.37	$453.24	$5,282.58	$56,166.54
	MODERATE $2,000-$24,999	$6,157.06	$888.30	$6,803.91	$49,701.87
	HIGH $25,000+	$55,197.12	$907.47	$10,435.51	$73,164.49
	TOTAL		$518.72	$6,325.46	$57,754.19
	AVERAGE	$3,090.36			$3,520.09
	TREND[12]		1.6%	2.7%	4.6%
					13.9%

We noted earlier that "High Cost" and "High Risk" are not synonymous. Within the Low Cost group is a subgroup of high risk members. The "high risk" members of the low cost group may be members who are recently diagnosed with a high cost condition, or whose condition is in remission, or (because healthcare costs tend to be episodic) are between treatment episodes. Returning to the definition of high risk with which we began the chapter, namely the *chance* of a significant loss with a high probability, we see clearly the high-risk members in the Healthy or Low Cost population are those members with the highest *probability* of transitioning to the Catastrophic or high-cost group. Conversely, within the Catastrophic group are low risk members with a high probability of a low expected loss. We will see throughout the book that risk prediction or predictive modeling is about the science of identifying the future trajectory of members who transition between cost categories.

1.3 WHAT IS THE DIFFERENCE BETWEEN RISK ADJUSTMENT AND RISK PREDICTION?

Risk adjustment and **risk prediction** (predictive modeling) are two closely related concepts. It is important, however, to understand the differences, which arise because the concepts use the same underlying principles but apply them to different problems. Risk adjustment is one (of several) technique that is used to normalize[13] populations; predictive modeling is used to

[11] PMPY: Per Member Per Year. PMPM: Per Member Per Month.

[12] The reader may be puzzled that the trend in the population (13.6%) is higher than trends within subpopulations. The reason for this is the shift in the distribution of members between subpopulations. This subject is analyzed in more depth in Duncan (2014) [2] and Bachler, Duncan and Juster (2006) [9].

[13] Normalization is an important component of many healthcare analytical exercises, and is often applied when comparisons are made between groups or populations that may represent different risks. Differences in risk profiles between populations being compared represent a confounding factor. One technique for eliminating the confounding due to differences in risk is risk adjustment.

make statements about the future.

There are essentially three major areas in which condition-based models are used in healthcare financial applications:

1. Program management:
    a. Identification of high-risk (future high-cost or high-utilizing) individuals for the purpose of enrolling the member in a care management program.
    b. Financial modeling and resource allocation for care management programs.
    c. Program evaluation—normalization of populations to compare outcomes or to calculate program savings.

2. Provider or health plan reimbursement:
    a. Population normalization (or standardization) so that providers or health plans may be reimbursed consistently for the risk that a population represents, rather than its actual resource utilization.
    b. Normalization of populations to allow evaluation of provider effectiveness and efficiency, perhaps as part of a pay-for-performance program.
    c. Profiling of providers to assess providers' quality and efficiency in terms of managing resource use of different types of patients.

3. Actuarial and underwriting functions:
    a. Pricing health plans or projecting future claims cost trends.
    b. Underwriting groups (where allowed) and projecting a group's future claims costs.

Risk adjustment is also called severity adjustment, intensity adjustment, or adjustment for health status. The underlying purpose of *adjustment* is to compare or normalize individuals and populations. Because of differences due to the types of risk factors discussed earlier, individuals and populations will use different amounts of healthcare resources. Certain analyses that are important to actuaries about utilization, pricing, provider quality and efficiency, or program efficacy and outcomes require comparison between equivalent populations. Risk adjustment is an increasingly prevalent technique for achieving equivalence between populations. Although not always used retrospectively, risk adjustment is often applied to historical data.

Case-mix adjustment is another method used for making fairer comparisons among health care providers or populations. Unlike risk adjustment, this technique does not require the development of a "score" based on the member's condition(s). It is a special case of a risk adjustment method, and we discuss an example here that both illustrates a method, and also shows a key shortcoming of case-mix adjustment that risk adjuster models are able to overcome because they reduce relative risk to a *score.*

Case-mix adjustment is a normalization technique that may be used as a component of an evaluation of variations in healthcare utilization and cost for provider groups, employer groups or physicians' patient populations for either the same year in which diagnoses were assigned (explanatory or concurrent) or in the future (prospective). Case-mix adjustment does not replace

the analysis of utilization or cost in different populations, but removes differences between the population risk profiles as a confounding factor in the comparison. Without adjustment for case mix, reports and ratings of hospital or physician care could be misleading. Furthermore, hospitals and other providers, in order to achieve higher rankings, would have an incentive to attract patients that have lower risk profiles and avoid riskier patients.

Table 1.4 illustrates the use of case mix to adjust for changes in a chronic population. In this case, the population may have one or more of five chronic conditions, so the number of permutations of conditions is explicit and may be enumerated, as we show in the table. This example is taken from Duncan (2014) [2].

See Iezzoni (ed.)(2003) [10] for more discussion of case-mix adjustment.

The example in Table 1.4 on the following page shows that the average PMPM cost of the population falls from the Baseline year to Year 1, from $725.99 to $697.04 (– 4%). This reduction is due in part to the change in population mix: the proportion of less-expensive members in the population (such as members with asthma) has increased, while that of more-expensive members has fallen (CAD, CHF and diabetes). Adjusting the Baseline population so that the mix of conditions matches the Year 1 population, the Baseline cost PMPM falls to$709.94 (a reduction of 2.2% or close to half of the observed reduction in member costs PMPM). This is a simple example showing that direct adjustment for member case mix is possible when the number of variables (five in our example) that have to be taken into account is not great. Once the full range of potential member conditions is considered, however, the method soon becomes unworkable. (With only 30 condition groupings, as in the DxCG Condition Categories, for example, there are over 1 billion potential combinations!) Thus methods that reduce the variations in member severity and conditions to a single arithmetic index or score are appealing and practical.

TABLE 1.4

Using Case Mix to Adjust Population Measures						
PMPM by Condition Group[14]						
	Average Cost PMPM Baseline	**Member Months Baseline**	**Member Distribution Baseline**	**Average Cost PMPM Year 1**	**Member Months Year 1**	**Member Distribution Year 1**
Asthma	$587.43	45,279	17%	$606.75	45,521	19%
CAD	$521.51	17,219	6%	$525.47	14,641	6%
CHF	$574.26	4,333	2%	$553.47	3,618	2%
COPD	$595.08	13,852	5%	$525.82	12,485	5%
Diabetes	$495.50	66,742	25%	$521.55	59,047	25%
Asthma & CAD	$698.99	2,205	1%	$688.11	1,791	1%
Asthma & CHF	$938.22	829	0%	$1,211.46	728	0%
Asthma & COPD	$858.41	15,748	6%	$763.01	14,143	6%
Asthma & Diabetes	$696.14	7,513	3%	$662.64	6,337	3%
CAD & CHF	$890.73	4,878	2%	$857.00	4,061	2%
CAD & COPD	$833.78	5,624	2%	$703.62	5,308	2%
CAD & Diabetes	$762.71	22,786	8%	$791.20	18,987	8%
CHF & COPD	$979.51	1,898	1%	$950.95	1,554	1%
CHF & Diabetes	$797.94	5,275	2%	$736.61	4,228	2%
COPD & Diabetes	$712.71	6,187	2%	$806.86	5,846	2%
Asthma & CAD & CHF	$1,026.22	597	0%	$917.79	719	0%
Asthma & CAD & COPD	$947.81	2,564	1%	$898.94	2,521	1%
Asthma & CAD & Diabetes	$921.92	2,089	1%	$916.60	2,091	1%
Asthma & CHF & COPD	$1,172.99	1,513	1%	$1,156.95	1,152	0%
Asthma & CHF & Diabetes	$1,046.79	1,044	0%	$788.90	761	0%
Asthma & COPD & Diabetes	$1,003.77	5,242	2%	$869.19	4,863	2%
CAD & CHF & COPD	$1,269.28	3,929	1%	$1,219.22	3,142	1%
CAD & CHF & Diabetes	$1,141.84	10,391	4%	$1,009.50	8,036	3%
CAD & COPD & Diabetes	$970.40	3,933	1%	$1,006.26	3,514	1%
CHF & COPD & Diabetes	$1,055.43	2,082	1%	$981.09	1,532	1%
Asthma & CAD & CHF & COPD	$1,708.55	2,017	1%	$1,456.85	1,533	1%
Asthma & CAD & CHF & Diabetes	$1,264.14	1,375	1%	$1,276.83	935	0%
Asthma & CAD & COPD & Diabetes	$1,065.95	2,257	1%	$1,235.85	1,906	1%
Asthma & CHF & COPD & Diabetes	$1,487.47	2,086	1%	$1,404.62	1,304	1%
CAD & CHF & COPD & Diabetes	$1,640.84	5,430	2%	$1,440.18	4,257	2%
Asthma & CAD & CHF & COPD & Diabetes	$1,799.27	3,765	1%	$1,716.11	2,510	1%
Total	**$725.99**	**270,682**		**$697.04**	**239,071**	
Re-weighted	**$709.94**					

[14] Abbreviations used in this table: CAD: Coronary Artery Disease (includes heart diseases that are sometimes referred to as "Ischemic Heart Disease"), refers to a narrowing of the arteries that may lead to blood clots or a heart attack. CHF: (sometimes referred to as "HF") is Congestive Heart Failure, caused by a weakening of the heart and its inability to pump blood around the circulatory system. COPD: Chronic Obstructive Pulmonary Disease is a disease of the airways (sometimes caused by smoking).

Unlike **risk Adjustment, risk prediction (**or **predictive modeling)** is more forward-looking. It capitalizes on the wealth of risk factor data available in patient profiles to predict which members (or member populations) have a high probability of experiencing losses or being higher utilizers of healthcare services in the future. This information can be valuable for high-risk program management, because it allows programs to target those with a high potential for utilization, or those who are at risk of experiencing a high-cost event or other loss. Predictive models may also be used for identifying the high-risk members in order to estimate the potential cost of an individual or group for rating purposes. The relatively high correlation between relative risk score and dollar claims (as identified in the Society of Actuaries Risk Adjuster Studies by Rosenblatt et al. [3]; Cumming et al. [4], Winkelman and Mehmud, 2007 [5] and Hileman et al. 2016 [10]) also allows the predictive risk score to be converted to dollars, the basis for group pricing and underwriting. A shortcoming of the use of a single risk score may be seen in the mechanical application of a risk score approach to a care management program. The highest risk scores are often found in patients with conditions that are not amenable to a management program (for example end-stage renal disease and certain cancers). We will explore the use of predictive modeling in program planning in Chapter 16.

In later chapters we will review the construction of different models that may be developed and used to generate relative risk scores, as well as some of the increasing number of applications.

APPENDIX: CLINICAL RISK – THE FRAMINGHAM HEART STUDY

The techniques that we develop later in this book apply generally to both financial and event risk. One well-known study of risk events is the Framingham Heart Study (www.Framinghamheartstudy.org). The Framingham study data have been used to develop models for predicting events associated with heart conditions, such as death, myocardial infarction, coronary insufficiency, angina, ischemic stroke, hemorrhagic stroke, transient ischemic attack, peripheral artery disease and heart failure. The study began in 1948 with a cohort of 5,209 men and women between the ages of 30 and 62 from the town of Framingham, Massachusetts, who had not yet developed overt symptoms of cardiovascular disease or suffered a heart attack or stroke. The Framingham study is unusual because it is both longitudinal[15] and has been conducted for more than 60 years. Over the years, careful monitoring of the Framingham population has led to the identification of both major risk factors, as well as valuable information on the effects of these factors such as blood pressure, blood triglyceride and cholesterol levels, age, gender, and psychosocial issues.

The Framingham study results were used to develop a predictive model for the probability of a cardiac event within a 10-year time frame. Models were developed for both males and females. The independent variables (risk factors) that predict the individual's probability of a heart attack are:

- Age
- Diabetes
- Smoking
- Treated and Untreated Systolic Blood Pressure (SBP)
- High-density Lipoprotein (HDL) Cholesterol
- BMI (Body Mass Index)

The 10-year risk for women can be calculated as $1-0.95012\exp(\sum_i \beta_i X_i - 26.1931)$ where X_i is the level for each risk factor and β_i are the regression coefficients of the risk factors. The risk for men is given as $.1-0.88936\exp(\sum_i \beta_i X_i - 23.9802)$.

Actuaries will recognize the complement of the Framingham prediction model (for example, $0.95012\exp(\sum_i \beta_i X_i - 26.1931)$ as an example of a survival model. As such, it predicts the probability of surviving without a cardiac event for 10 years. Others will recognize this as an example of a Cox-type model. Readers who want to know their own heart risk score can find calculators online, for example at http://cvdrisk.nhlbi.nih.gov/. The models and model coefficients are given in Table A1.

[15] A longitudinal study follows its subjects over a period of time. In U.S. healthcare research, because of the limited availability of data over long periods, a study is more likely to be cross-sectional, that is, to compare subjects with different characteristics at a point in time. Most studies of healthcare data are cross-sectional and are limited to the period covered by claims data, rarely more than three or four years.

TABLE A1: REGRESSION COEFFICIENTS AND HAZARD RATIOS[16]

Men (10-year Baseline Survival: $S_0(10) = 0.88936$)				
Variable	**Beta***	**p-Value**	**Hazard Ratio**	**95% CI**
Log of Age	3.06117	<.0001	21.35	(14.03, 32.48)
Log of Total Cholesterol	1.12370	<.0001	3.08	(2.05, 4.62)
Log of HDL Cholesterol	-0.93263	<.0001	0.40	(0.30, 0.52)
Log of SBP if not treated	1.93303	<.0001	6.91	(3.91, 12.20)
Log of SBP if treated	1.99881	<.0001	7.38	(4.22, 12.92)
Smoking	0.65451	<.0001	1.92	(1.65, 2.24)
Diabetes	0.57367	<.0001	1.78	(1.43, 2.20)

Women (10-year Baseline Survival: $S_0(10) = 0.95012$)				
Variable	**Beta***	**p-Value**	**Hazard Ratio**	**95% CI**
Log of Age	2.32888	<.0001	10.27	(5.65, 18.64)
Log of Total Cholesterol	1.20904	<.0001	3.35	(2.00, 5.62)
Log of HDL Cholesterol	-0.70833	<.0001	0.49	(0.351, 0.691)
Log of SBP if not treated	2.76157	<.0001	15.82	(7.86, 31.87)
Log of SBP if treated	2.82263	<.0001	16.82	(8.46, 33.46)
Smoking	0.52873	<.0001	1.70	(1.40, 2.06)
Diabetes	0.69154	<.0001	2.00	(1.49, 2.67)

* Regression Coefficient.

[16] From Framingham Heart Study website, https://www.framinghamheartstudy.org/risk-functions/cardiovascular-disease/10-year-risk.php

2 MODELS FOR PREDICTING HEALTH COSTS

2.1 INTRODUCTION

In Chapter 1, we introduced the concept of health risk and the important observation that, while a population may have stable costs over time, within a population, a significant number of members transition between different risk states and cost levels. The ability to identify those members with a high probability of transitioning (either upward to a more expensive group or downward to a less expensive group) through **predictive modeling** is potentially valuable information to managers of health risk pools. It allows for proactive intervention, either to price the risk more accurately or to target medical management and population health management interventions aimed at changing the cost trajectory. Conversely, the ability to correlate members' cost with their health conditions allows us to compare populations on the basis of their normalized costs, through **risk adjustment**.

The earlier that the high risk member is identified and the more accurately the member outcome may be predicted, the more valuable the information. This has led to considerable effort in the industry to capitalize on new and more accurate sources of healthcare information and the ability to perform earlier intervention and more accurate pricing. Even without some of the newer techniques and data, however, it is possible to construct traditional risk adjusters and predictive models that will add value to actuarial functions such as pricing, underwriting,[1] provider network contracting or outcomes evaluation. We will call these "Non-condition risk-based" models, to distinguish them from the newer, condition risk-based models, which we will address in Chapter 4.

2.2 NON-CONDITION RISK-BASED MODELS

Alternative tools and techniques exist for assessing and accounting for risk. How do health-based risk adjustment and predictive modeling compare to actuarial and other methods of predicting claims costs? In this section we apply different techniques to the same groups to illustrate how non-condition-based risk factors may be used to rate groups. The treatment here is theoretical, to illustrate the principle. Since the first edition of this book, the passage of the Affordable Care Act[2] has prohibited the application of these techniques. Nevertheless, we will consider the role of risk identification in groups as an introduction to later discussion of risk adjustment. Even though underwriting is no longer possible in the small group and individual

[1] To the extent that this is still permitted.

[2] The Patient Protection and Affordable Care Act is actually in two parts: the Patient Protection and Affordable Care Act (P.L. 111–148—March 23, 2010) and the Health Care and Education Reconciliation Act [11].

markets, the techniques discussed here are useful for premium rate setting for those markets, as well as for setting premium equivalent rates for large groups.

Traditionally, actuaries have predicted the likely future cost of an individual or of the group of which the individual is a member using one (or a combination) of the following techniques:

1. **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. Table 2.1 shows the relative costs (allowed charges) of different age and sex categories taken from the Solucia Consulting[3] benchmark database (a large national database). All data are from 2007, so amounts are low by current standards, while relativities are still reasonable. See footnote 8 in chapter 1; to convert to more current costs the reader may wish to double these numbers.

TABLE 2.1

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

For underwriting and pricing purposes, such relative claims are often converted into factors that may be applied to a particular population's demographics to derive its overall risk "score." Assuming that the insurer's entire book of business has a score of 1.00, a rate may then be established for a specific group (and individuals within a group) based on the group's risk relative to that of the book of business of which it will be a member. This is demonstrated in Table 2.2. The relative risks and the costs derived from them may, however, not be accurate in the case of an individual member, as we shall see later.

[3] Now SCIO Health Analytics, www.sciohealthanalytics.com.

TABLE 2.2

Age/Sex Relative Cost Factors			
	Male	**Female**	**Total**
< 19	0.46	0.44	0.45
20-29	0.42	0.88	0.65
30-39	0.56	1.09	0.83
40-49	0.82	1.18	1.01
50-59	1.41	1.57	1.49
60-64	2.08	2.05	2.06
Total	0.89	1.11	1.00

Age/sex factors are frequently applied to groups to develop a manual rate for the group. An example of the calculation is provided in Table 2.3.

TABLE 2.3

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

Assuming that our underlying manual (book of business) claims are expected to be $3,090 per year, this group is predicted to have costs of $0.94 \times \$3,090$ or $2,905. This simple method is universally applied, but its principal drawback is that it ignores information that may exist about the population's *clinical* risk burden and the likely future development of costs from those risks, and is thus not as accurate as methods that consider clinical risk.

The ability to predict future costs accurately using age/sex factors may be seen in Table 2.4. In this example, we apply age/sex factors to randomly selected groups from the same population and costs that we developed in Table 2.1 in order to compare the relative accuracy of age/sex cost prediction for continuously-enrolled members of employer groups. To illustrate the technique, we limit the comparison (for simplicity) to the same continuously-enrolled members that we used in Chapter 1. Obviously, in a real-world situation, some members would leave the group and there would be new entrants, which

would tend to increase the variances between actual and predicted costs. Because these are commercial groups, we also excluded (for this example) members who turned 65 in the subsequent year from both the baseline and subsequent year calculations.

To develop Table 2.4, we first calculate average age/sex risk factors for the group in each year based on the group's demographics, as well as the ratio of the age/sex factor for each group relative to the age/sex factor for the entire book of business. We also know (from Chapter 1) that the overall trend for the book of business is 13.9%, so we project a claims cost for the book of business as the baseline cost plus trend. Depending on the source of our trend estimate, we might want to include an estimate of the change in age/sex factor from baseline to subsequent year as well. In our case, the effect of aging is already included in the overall trend estimate in Chapter 1, so we do not include a separate estimate. We estimate each employer group's cost as its age/sex ratio multiplied by the book of business average cost for the subsequent year.

TABLE 2.4

Demographic Factors as Predictors of Future Health Costs

		Age/Sex Factors		Factor Ratio			Difference** (Predicted-Actual)	
Employer	Number of lives	Baseline	Subsequent Year	Subsequent/ Average	Predicted Cost*	Actual Cost	$	%
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	

* Predicted Cost = Baseline Cost × Trend × Subsequent Year/Baseline Year Relative Age/Sex Factor. Thus (for example) predicted cost in the Subsequent Year for employer 1 =

$$\text{Average Baseline cost } (\$3{,}090) \text{ x Trend } (1.139) \text{ x } \frac{\text{Subsequent Year Age/Sex Factor (group)}}{\text{Subsequent Year Age/Sex Factor (population)}}$$

$$= 3{,}090 \text{ x } 1.139 \text{ x} \left(\frac{1.42}{1.03}\right) = \$4{,}853$$

** In this example, due to the way we have established our rates to equal the average cost for the book of business, the result is a zero overall difference. This is unlikely to occur in practice.

It is worth noting some interesting observations from Table 2.4. First, age/sex is a poor Stechnique in some cases, but better in others. For relatively large groups and groups where the underlying demographics are similar to those of the book of business (age/sex factors closer to 1.00), the estimate is reasonably close (groups 2, 4, 5 and 7, for example). Where the group is smaller or significantly older (groups 1 and 6, for example) the age/sex factors are a poor estimator of future cost. Since older members are more likely to develop health conditions, the divergence at older ages is not unexpected. The divergence in small groups is one reason that small groups are rated on a credibility-weighted combination of experience and manual rates, as we shall see in a moment. Credibility weighting is a standard actuarial technique that allows actual experience of a group to be taken into account in developing rates, while recognizing that a smaller group's experience is more subject to random fluctuations than a large group's experience. See Skwire (2016) [12] or Herzog (1994) [13] for more detail.

2. **Prior Cost (prior year's claims)**: prior cost is one the most frequently used risk predictors for pricing and underwriting, and is also often used for selecting candidates for care management programs. The results in Table 1.2 should have demonstrated that prior high cost is not a particularly accurate predictor of future high cost at the individual level, although as a predictor it performs much better at the group level, particularly for larger, credible groups. In Table 1.3, only one-third of the high-cost group remained high cost in the subsequent year; 18% of all high cost members in the subsequent year were in the low cost group in the baseline year. As we see in Table 2.5, this observation at the individual level is offset when other group members are included, particularly in larger groups. In Table 2.5, we take each group's baseline cost PMPM and trend it to the subsequent year using the 13.9% experience trend factor from Table 1.2. As Table 2.5 shows, the results are less subject to the variation that we saw in some groups in Table 2.4, and prior cost can be a reasonably accurate predictor at the group level, particularly for larger groups.

TABLE 2.5

Prior Cost as a Predictor of Future Health Cost						
		Cost PMPY			Difference vs. Actual	
Employer	Number of lives	Baseline	Subsequent Year Predicted*	Subsequent Year Actual	$	%
1	73	$27,488	$31,313	$23,902	$7,412	23.7%
2	478	$2,637	$3,004	$2,693	$311	10.4%
3	37	$1,050	$1,196	$1,339	**($143)**	**–12.0%**
4	371	$2,493	$2,840	$3,325	**($485)**	**–17.1%**
5	186	$3,377	$3,846	$3,345	$501	13.0%
6	19	$11,352	$12,932	$10,711	$2,221	17.2%
7	359	$2,008	$2,288	$3,401	**($1,114)**	**–48.7%**
8	543	$2,598	$2,960	$3,667	**($707)**	**–23.9%**
9	26	$3,022	$3,443	$5,181	($1,738)	-50.5%
…	…	…	…	…	…	…
Average		$3,090	$3,520	$3,520	$ 0	0%
Sum of Absolute Differences (9 sample groups only)					$14,632	

* Calculated as Baseline PMPY × Trend.

3. **Combination of Age/Sex and Prior Cost**: particularly for rating smaller groups, a combination of prior cost and age/sex rating is often used, with the proportions of each in the final calculation being driven by the credibility assigned by the underwriter to the size of the group (and sometimes to the validity of its data). The combination of both approaches produces more accurate predictions than either method used separately. For the purpose of illustration in Table 2.6, we assume that a 2,000 member group (24,000 member months) is fully credible, and that credibility is applied as follows:

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

where $Z = \left(\frac{N}{2000}\right)^{0.5}$ and N is the number of members in the group.

As we see in this example, the deviation of some groups is reduced and that of others increases when we apply credibility weighting. We will compare the three methods side by side in Table 2.7.

TABLE 2.6

Combination of Age, Sex, and Prior Cost as a Predictor of Future Experience							
			Cost PMPY			Difference vs. Actual	
Employer	No. of lives	Credibility[4] Factor	Baseline	Subsequent Year Predicted	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)**	**–53.6%**
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	

2.3 AGE/SEX AND PRIOR COST MODELS: SUMMARY

We have described three commonly-used methods for evaluating and pricing health risk: age/sex, prior cost and a credibility-weighted combination. The accuracy of all three methods improves as the size of the group increases. When groups appear to contain members who are outlier claimants, the prior cost method can be more accurate, provided the experience that drives the member's claims persists. In Table 2.7, we compare the results of the three methods. Interestingly the prior cost method produces both the lowest total difference and the lowest total absolute difference. As a predictor, it appears to perform better than the credibility-weighted method, although this performance is largely the result of deviation in one relatively small group. If we exclude that group, the performance of all three methods becomes much closer, with the credibility-weighted method performing marginally better on an absolute basis and the prior cost method performing better on a total cost basis.

[4] For a detailed discussion of Credibility as it is applied to underwriting and pricing, see Skwire (2016) [12].

TABLE 2.7

Comparison of Three Risk-Rating Methods							
		Difference (Predicted-Actual)					
		Age/Sex		Prior Cost		Credibility-Weighted	
Employer	Number of Lives	$	%	$	%	$	%
1	73	**($19,049)**	**–393%**	$7,412	24%	**($13,994)**	**–141%**
2	478	**($102)**	**–4%**	$311	10%	$100	4%
3	37	$1,626	55%	**($143)**	**–12%**	$1,385	51%
4	371	$6	0%	**($485)**	**–17%**	**($205)**	**–7%**
5	186	$170	5%	$501	13%	$271	8%
6	19	**($4,383)**	**–69%**	$2,221	17%	**($3,739)**	**–54%**
7	359	**($87)**	**–3%**	**($1,114)**	**–49%**	**($522)**	**–18%**
8	543	**($398)**	**–12%**	**($707)**	**–24%**	**($559)**	**–18%**
9	26	$414	7%	**($1,738)**	**–50%**	$169	3%
…		…		…		…	
Average		$ -	0.0%	$ -	0.0%	$ -	0.0%
Sum of Differences		($21,803)		$6,258		($17,094)	
Sum of Absolute Differences		$26,235		$14,632		$20,944	

2.4 RISK FACTOR-BASED RISK MODELS

The traditional models discussed in Section 2.1.1 have in common that they predict health cost and risk without using information about individual member risk factors. Age is clearly a proxy for medical condition-based risk, but as the results show, not a particularly accurate one, even when member risks are grouped. As we discussed in Chapter 1, it may be possible to make more accurate predictions if we incorporate additional risk factors into our modeling.

Typical predictive modeling techniques rely on incurred claims. The detail contained in claims makes the risk adjustment and predictive modeling based on this data reasonably reliable. On the other hand, we only have a limited ability to predict the cost of members in the absence of claims (such as in the case of a newly-insured group) or before the member files his first claim. This is particularly challenging for lifestyle diseases, because many diseases have limited or no associated medical precursors. This has led some analysts to develop newer techniques based on non-traditional or exogenous data, which we shall discuss later. We will discuss risk factors that can be derived from three different sources of data:

1. Medical condition-related risk factors derivable from claims, such as diabetes or cancer. Members with chronic medical conditions clearly will generate higher claims than members who do not have those medical conditions.

2. Lifestyle related risk factors derivable from self-reported data, such as smoking, stress, lack of exercise, poor nutrition, poor seat belt use, scuba diving or auto racing. Some of these risk factors may have a short-term impact on member cost such as an auto accident; other factors, such as obesity or smoking, may take years to have a pronounced effect on member health, generally leading to the emergence of chronic medical conditions. For an actuarial survey of the mortality and morbidity associated with smoking and obesity see Sam Gutterman [14, 15].

3. Lifestyle-related risk factors that are derivable from external or exogenous risk factors, such as the industry in which an individual works, the location of his home, his education level, household income level or insurance coverage.

The remainder of this chapter discusses the underlying theory of risk factors and the incorporation into predictive models.

2.5 MEDICAL CONDITION-BASED RISK

Different medical conditions impose different healthcare risks and costs. We illustrate this principle in Table 2.8 with some sample lives from our test database. The "Standardized Costs" are those developed for different age/sex combinations in Table 2.1 from the Solucia Consulting Benchmarking database.

TABLE 2.8

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%

The examples in this table illustrate a number of points about medical condition-based risk. First, we see clearly that the existence or absence of a health condition causes deviation from the standardized (average) member cost in the last column. Members at any age that have no conditions cost less than the standardized cost for the age/sex group. Members with chronic or acute conditions cost considerably more. This example also illustrates the principle of additivity:

- The 40-year-old male whose only health risk is a heart condition experiences a cost of $18,185.
- The 45-year-old male whose only health risk is a diagnosis of diabetes experiences a cost of $5,024.
- The 40-year-old male with diagnoses of both a heart condition and diabetes experiences a cost of $23,479.

In this particular example, the effect of heart condition and diabetes diagnoses is additive. Experience shows, however, that some condition interactions could also result in cost efficiencies (total cost being less than the sum of individual condition costs) while others could result in cost reinforcement (total cost being greater than the sum of individual costs).[5]

Finally, there is considerable variance in the cost of the same condition at different ages. In the case of the members with diabetes-only diagnoses, the older member has a higher cost than the younger member. In the example of diagnoses of breast cancer and other conditions, the older member's cost is lower. This variance could be due to a number of factors, including difference in severity of the diagnosis, treatment of the patient, duration since first diagnosis (since the severity of a diagnosis tends to increase over time, particularly if not treated regularly) or other conditions that are not specified in the "other conditions." In Chapter 4, we shall explore in more detail the relationship between different levels of severity and cost.

One note of caution about the numbers in Table 2.7—the members in this table have been selected to illustrate the relative costs of members with certain conditions. For some of these members, the costs relative to the standardized (age/sex) costs are high. The relative frequency of these high-cost members is low, however, as Table 1.2 shows. Thus, the principle of insurance continues to operate—many relatively low-cost members will subsidize the relatively few high-cost members.

As the above example shows, there is considerable information contained in the member's diagnosis. As we shall show, this information allows us to build more accurate models to predict an individual's or group's cost, and to reduce the differences observed in Tables 2.4 through 2.7.

2.5.1 APPLICATION OF MEDICAL CONDITION-BASED RISK

In section 2.1.1 we looked at the outcome of using different risk-assessment methods (age/sex, prior cost and a combination). To complete the discussion, in this section, we look at the application of condition-based risk in the same population. We applied a commercial

[5] In more sophisticated models that allow for interactions between variables, the joint effect of two conditions may be non-linear.

grouper model[6] to derive a condition-based average prospective risk score for each group. Each group's relative risk score is calculated as the group's risk score relative to the overall risk score for the book of business. The expected cost PMPY for each group is then calculated as the average cost for the book of business multiplied by the group's relative prospective risk score. Results of this calculation are shown in Table 2.9.

TABLE 2.9

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 Differences (9 sample groups only)					$6,437	
Sum of Absolute Differences (9 sample groups only)					$12,118	

Condition-based models generally perform well. The sum of the differences is similar to that of the prior cost model in Table 2.7 while the overall sum of absolute differences (used here as an indicator of overall differences, rather than as a statistical test) is the smallest for this method, indicating that the inclusion of condition-based risk has reduced the overall variance between actual and predicted cost. We emphasize, however, that the 9 groups illustrated here were selected to represent a (non-statistical sample) cross-section of the population, and that a different sampling of groups may show different results for the different methods.

[6] The derivation of risk scores in commercial grouper models is, in principle, a similar process to that illustrated in Table 2.8. See chapter 5 for a discussion of grouper models and the derivation of risk scores.

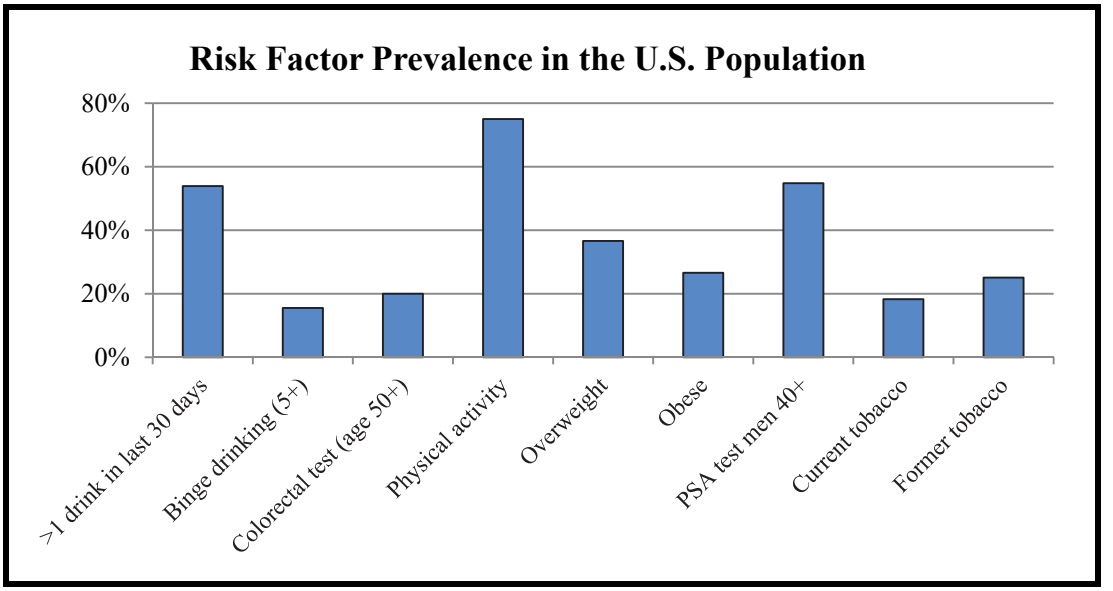
2.6 LIFESTYLE-RELATED RISK FACTORS

We discussed medical condition-based risk in Section 2.2. Health plans have always been aware of non-condition risks that affect cost, such as geographic or industry factors. Health plans have, in recent years, become aware that risk is broader than their traditional focus on medical conditions and underwriting factors, and that the broader set of risks needs to be considered. It is well established that lifestyle behavior is associated with higher-cost illnesses such as obesity (and its attendant conditions, such as diabetes), smoking, high blood pressure, and heart disease. "Wellness" is a relatively new set of intervention programs. One component of wellness is the health risk assessment (HRA), a questionnaire that is completed by participants at the start of the program to identify risk factors in the population, and to provide a baseline for assessing progress during the intervention program.

Lifestyle-related risk factors are highly prevalent in the population, as the following chart (derived from the U.S. Centers for Disease Control and Prevention data) demonstrates. A typical HRA covers the following risk factors:

- Personal Disease History: presence of a diagnosis of Asthma, Cancer, Depression, Heart Disease, High Blood Pressure, Stroke, and other selected high cost diseases.
- Family Disease History: diagnosis of Cancer, Heart Disease, High Blood Pressure, Stroke, etc.
- Health Screenings and Immunizations: Influenza, Pneumonia, etc.
- Alcohol Consumption: ability to limit drinking in various stressful situations.
- Injury Prevention Behavior: gun safety, wearing seat belts, etc.
- Nutrition: consumption of grains, nuts, dairy, and respective portions.
- Physical Activity: low, medium, and high intensity.
- Skin Protection: use in outdoor activities.
- Stress and Well-Being: ability to handle stressful situations.
- Tobacco Use: cigar vs. pipe vs. cigarette, how many, how addicted.
- Weight Management: Body Mass Index.
- Women's Health: pregnancy status, receiving hormone replacement therapy.

Some of these data elements, particularly diagnostic information, procedures, or tests, may be obtained from claims. Biometric information may be obtained from physicians or biometric screening companies. Other information may only be obtained from the member (self-reported data).



Source: Centers for Disease Control and Prevention (CDC). *Behavioral Risk Factor Surveillance System Survey Data.* Atlanta, Georgia: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention**,** (2008)**.**

FIGURE 2.1

The relationship between risk factors and claims data, as shown in Figure 2.2, illustrates the opportunity provided by lifestyle and self-reported risk factors in constructing a predictive model or adding to the predictive accuracy of an underlying condition-based model. One of the best-known studies of the correlation between risk factors and claims costs is the HERO study (Goetzel, (1998) [16]). One of the more confusing aspects of non-claims-based risk assessment is the lack of consistency in questionnaires, definition of risks, and assessment of relative risk. Figure 2.2 shows the assessment of the "HERO" data (Health Enhancement Research Organization, www.the-hero.org) in the 1998 paper by Goetzel and others. They assign members to "high" and "low" risk categories based on responses to a health risk assessment questionnaire administered between 1990 and 1995. Claims were expressed in 1996 dollars.

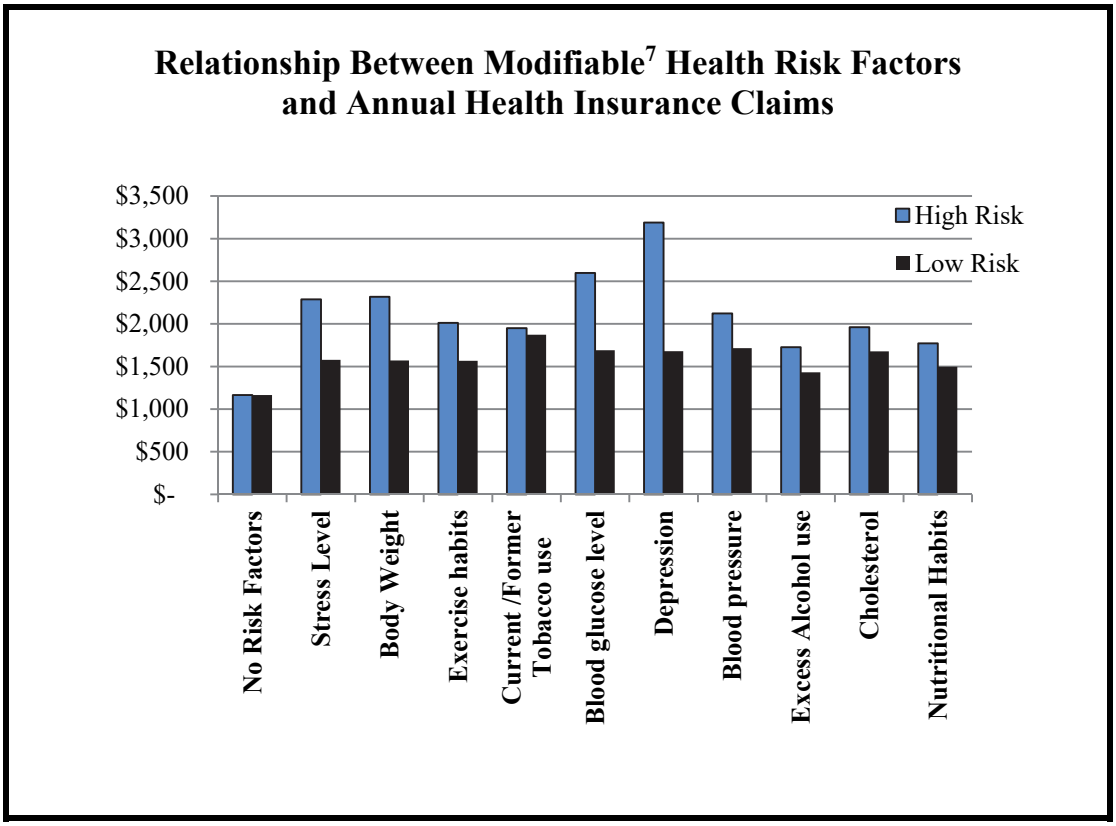


FIGURE 2.2

The study in Figure 2.3 shows the incremental cost associated with each risk factor for the high-risk members from the same data as Figure 2.2. The highest incremental costs are associated with developed health conditions (depression, heart disease, stroke, psycho-social conditions), but the lifestyle-related conditions are also significant. The interaction between different independent variables and costs, however, is not clear. The calculated costs associated with different risk factors are lower than those reported in the 1998 study.

In Table 2.10, we show the range of responses and corresponding claims values for a sample of risk factors. The values are taken from an analysis of relationships between self-reported risk factors and claims in a large commercial healthcare population, as reported in Duncan (2014) [2] *Managing and Evaluating Healthcare Intervention Programs*, and all represent a one-year cost. Risk factors are generally reported as categorical variables (Body Mass, for example, is reported as one of seven values). All risk factors are additive, meaning that there is a baseline cost for individuals who have no risk factors, and additional cost is imposed depending on the incidence and level of an individual's risk factors. The mean values for associated annual health costs are illustrated in Figure 2.4.

[7] Modifiable risk factors are those over which an individual has some control (for example, body weight, or smoking) rather than risk factors that are not controllable by the individual (e.g., most condition-based risks).

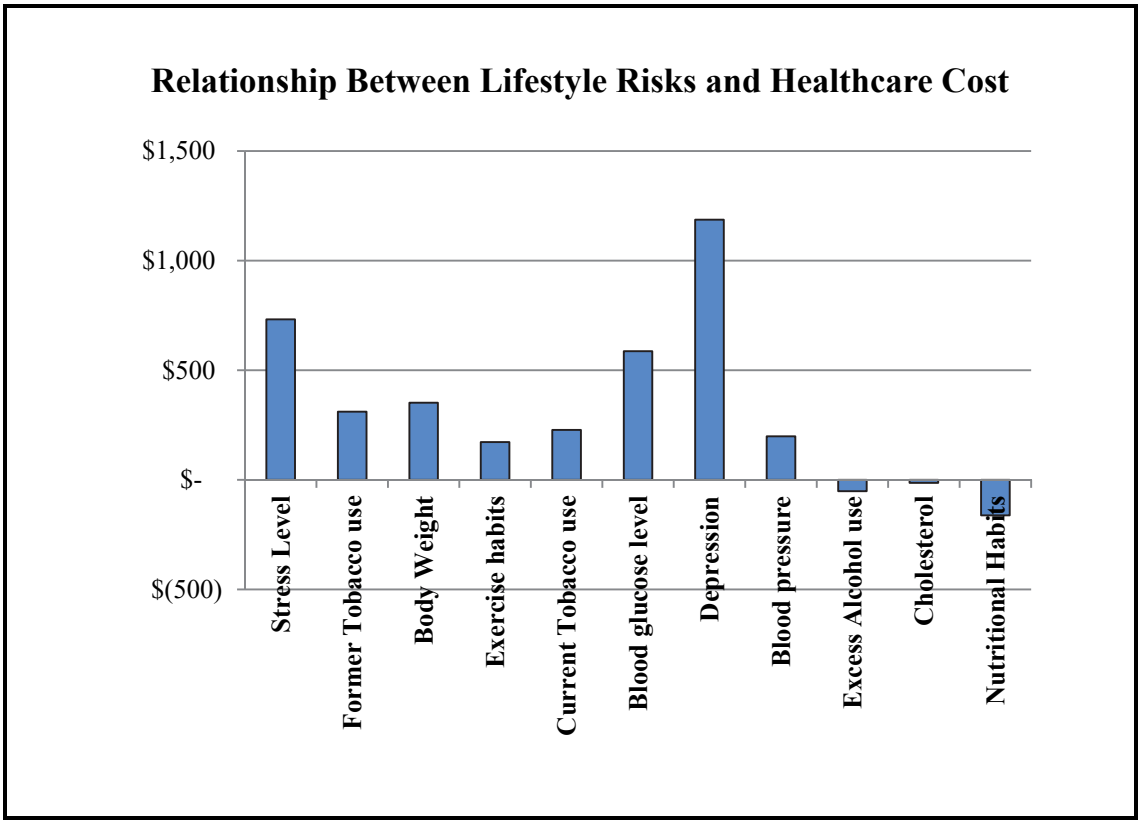


FIGURE 2.3

Data are in 1996 dollars. Source: Anderson, DR et al. (2000) [17].

TABLE 2.10

Examples of Risk Factors and Related Costs			
Risk Factor	**Description**	**Response Categories**	**Associated Annual Health Costs**
Personal Disease History	Have you ever been diagnosed with any of the following: Congestive Heart Failure (CHF), Osteoporosis, Angina, TIA (Transient ischemic attack, or a mini-stroke lasting less than 24 hours)	Yes	$203
Weight Management	Body Mass Index group	1 (< 25), 2 (25-29.99) 3 (30-34.99) 4 (35-39.99) 5 (> 40, no value)	$529 $1,058 $1,587 $2,116 $3,703
Immunizations	Have you had a PSA test (prostate specific antigen) within the last 12 months?	Yes	$370
Immunizations	Pneumonia	No	$247
Stress and Well-Being	In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?	1 (Never) 2 (Almost Never) 3 (Sometimes, no value) 4 (Fairly Often) 5 (Very Often)	$408 $816 $1,224 $1,632 $2,040
Physical Activity	Low-intensity physical activity – days per week	1 (Never) 2 (Almost Never) 3 (Sometimes, no value) 4 (Fairly Often), 5 (Often) 6 (More Often) 7 (Most Often)	$0 **($784)** **($1,176)** **($1,568)** **($1,960)** **($2,352)** **($2,744)**

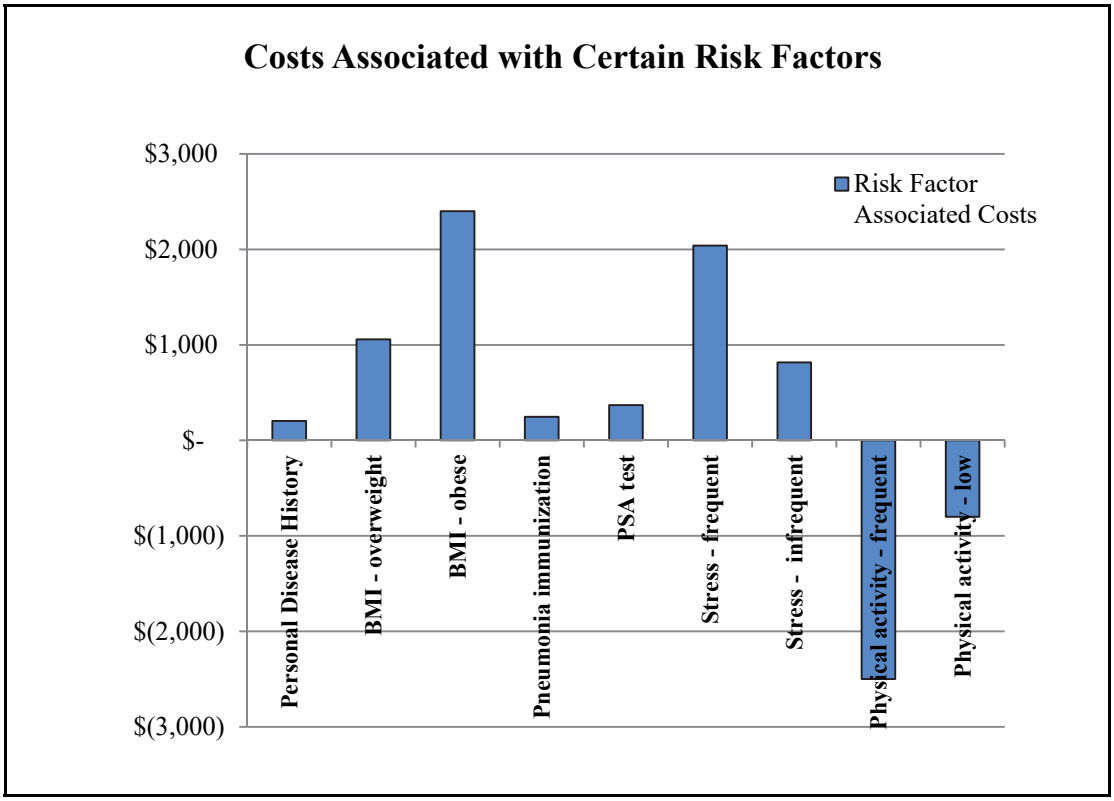


FIGURE 2.4

2.7 EXOGENOUS RISK FACTORS

Lifestyle-based analytics is a relatively new form of predictive modeling in actuarial work that analyzes extensive data sets, including traditional data sources such as demographics and claims, but supplements this with the large consumer databases that are now available. Within the last 10 years, the abundance of readily available consumer data has dramatically changed the way most organizations attract and interact with their customers. From financial services organizations to direct retailers to supermarkets, companies are using third-party consumer datasets to help with everyday decision making by understanding their prospects and customers with a new level of detail not previously available.

The cost of data storage has decreased exponentially over the last 25 years. In the early 1980s, the cost of a 5-megabyte hard drive was about $3,500, or the equivalent of $700,000 per gigabyte. By the early 1990s, Western Digital 50-megabyte hard drives were selling for about $600, or $12,000 per gigabyte. Today, you can purchase a multi-terabyte drive for about $160, or $0.04 per gigabyte.[8] With this decrease has come an exponential rise in the amount of information that is being stored about individuals. An approximate measure of the

[8] A reduction even from the first edition of this book (2011) which reported $0.20 per gigabyte.

average amount of information stored for any particular individual is estimated by disk storage per person (DSP) measured in megabytes/person/year. In 1985, DSP was estimated at 0.02, grew to 28 in 1996, increased to 472 in 2000 and most recently it has been estimated to be significantly higher, at 3,500.

Currently, more than 95 percent of the households in the United States have substantial amounts of publicly available consumer data tied to their addresses. The data comes from a wide variety of sources: the U.S. Census, public records (deed and registration), financial services (banking, credit/debit cards, and mortgages), warranty and registration cards, purchases, Internet transactions, affinity programs and transaction cards (supermarket cards and frequent-buyer programs), as well as a vast variety of other sources. The cost to obtain third-party consumer data has also decreased over time. Currently, several hundred individual data fields, more than enough to run a lifestyle-based risk model, will cost the purchaser no more than the cost of a stamp per individual (approximately $0.50).

The emergence of affordable, integrated consumer data provides an opportunity to employ lifestyle and psychographic trends for predictive modeling, risk adjustment, and population health management. Most of us are familiar with the direct marketing companies who use this data to profile consumers for product offerings (e.g. credit cards or consumer goods). Similarly, the majority of consumer data usage in the health care marketplace today has centered on marketing and sales applications. Direct-to-consumer marketing efforts are using consumer data in numerous ways. One insurance company, for example, specializing in senior products has developed its own internal database that contains the consumer data metrics for every U.S. citizen over the age of 50. This database is constantly tested, mined, and re-evaluated with each mailing or direct agent contact recorded. The company has increased prospect response rates over tenfold.

Beyond the traditional marketing and customer retention uses for these consumer data sets lies an embedded value in using this data for enhancing risk analysis. Health insurers have been slow to integrate their consumer, customer service, and marketing efforts with their predictive modeling and other analytics initiatives. This is an area that should grow and provide greater opportunities for actuaries experienced in analytics and predictive modeling in the future. Many of the choices people make (whether consciously or unconsciously) every day have an impact on the individual's risk of disease. Traditionally, health insurers have surveyed their populations to acquire the details of many of the lifestyle risk factors (smoking, obesity, etc.). This approach has been both expensive and relatively low-yielding (unless the health plan or employer provides significant incentive for completion of the survey).

On the other hand, third-party consumer data sets are readily available and many of the traits that health plan managers would like to know about their customers can be obtained from these sources. Examples of data elements that may be obtained or derived from external sources include food purchases (fast food, diet food, vegetarian, gourmet), self-improvement

(health/fitness, dieting/weight loss), fitness activities (aerobics, running, walking, tennis, golf), physical inactivity (television time, computer time, video games, social media), stress indicators (financial problems, family size and status, occupation), tobacco preferences, alcohol purchases, foreign and domestic travel, and vehicle type, to name but a few.

It has been well documented in numerous medical journals that poor nutrition and inactive lifestyles tie to obesity and related diseases. These risk factors are also correlated with osteoporosis, osteoarthritis, rheumatism, lower back pain, and other issues. Stress is linked to depression, back pain, obesity, cardiovascular, and other diseases and medical conditions. Pregnancy, a medical condition rather than a disease, is yet another highly predictable circumstance and is based on factors such as age, family size, ages and gender of current children, family status, and financial indicators. Relationships between these exogenous factors and medical conditions can be used for risk adjustment and predictive modeling. Additionally, there are relationships between geographic, income, demographic, family size, employment and other factors that are not usually collected for predictive modeling purposes, and yet are available from external data sources and may be integrated into a broader predictive modeling exercise. Lifestyle-based analytics may be used to identify both healthy and unhealthy individuals, supplementing traditional (claims- or age/sex-based) predictive models. Unlike health risk assessments, lifestyle-based analytics do not require applicants to fill out a form or employers to provide incentive programs to encourage the application process. In addition, they are not subject to the inaccuracy of a self-reported application involving personal information. Since lifestyle-based analytics do not require any medical information, they are HIPAA compliant and therefore need no authorization by individuals.

As the prevalence of obesity, diabetes, cardiovascular and other lifestyle-related diseases continues to increase, more and more emphasis is being devoted to population health management.[9] Although many disease management programs have been demonstrated to be effective in reducing overall medical costs, many believe that the biggest potential for cost savings will be through effective population health management programs. Historically, such programs have been fairly generic in content and delivered to the entire population. Despite the effectiveness of such programs, this broad-based approach has often met with limited success in identifying and enrolling the right members. An example of the economic challenges facing employers who want to offer a population or wellness program is the company that offers to reimburse 50% of the cost of gym memberships for its employee population, only to have the healthy employees participate, resulting in considerable expense to the employer but only a very limited future reduction in medical costs.

[9] Population Health Management describes intervention programs (such as wellness) that aim to manage the health status of members of an entire population. Population Health Management may be distinguished from specific intervention programs such as Case Management that often address specific clinical needs in targeted subsets of the population.

Lifestyle-based analytics are valuable as a means of segmentation of the almost 70% of the population that is otherwise indistinguishable when looking at medical claims history. Third-party data can be used to identify the tri-athlete, the pre-diabetic couch potato, and everyone in between. Using this information, population health management programs can now target the riskiest individuals, identify which modifiable risk factors are present in which members, and implement customized programs to help specific individuals minimize their health risks.

A recent development in lifestyle analytics has been the focus on "big data" derived from social media and other sources. "Every minute, Facebook users share 2.5 million pieces of content, Youtube users upload 72 hours of content, and Apple users download 50,000 apps. That's every *single minute*."[10] The challenge with all this data is distinguishing signal from noise, and while data miners have made inroads into this data, mostly for consumer product recommendations, health companies have been slow to take advantage of its opportunities. Still, as Ronald Reagan is reported to have said "With all this manure, there must be a pony in here somewhere! "[11]

Health insurers have been slow to integrate their consumer, customer service and marketing efforts with their health risk predictive modeling activities such as underwriting. As state and national regulators continue to restrict the use of underwriting as a way to differentiate risk, more and more healthcare companies are now looking to other means to help understand risk segmentation and develop unique solutions to better understand and address. This is an area that should grow and provide greater opportunities for actuaries experienced in analytics and predictive modeling in the future.

The predictive accuracy of lifestyle-based analytics has not been evaluated in healthcare on the same basis as claims-based models, such as the Society of Actuaries evaluations, although the Society of Actuaries has recently completed a project to do so (Mehmud, 2013) [18]. The use of predictive modeling and alternative data such as lifestyle data and credit scores has been included in Property and Casualty risk analysis for over 12 years and is now standard practice. Companies such as Progressive Insurance use data to segment their customer base for pricing purposes, and are using device-reported technology to track driving habits, rewarding good drivers and penalizing those that drive unsafely. In addition, over the last several years, life insurance companies have been actively pursuing predictive modeling and alternative data, so much so that the Society of Actuaries is funding studies and collecting experience on the use of automated underwriting, predictive modeling, and alternative datasets. The innovative U.S.-based provider of a workplace health promotion and wellness program, The Vitality Group (www.thevitalitygroup.com) has partnered with several insurance companies to use lifestyle- and device-reported data to provide customers who exhibit a healthy lifestyle a discount on their life insurance rates. In

[10] Reported at https://aci.info/2014/07/12/the-data-explosion-in-2014-minute-by-minute-infographic/
[11] From *How Ronald Reagan Changed My Life* by Peter Robinson. Regan Books, 2003.

healthcare, the ability to combine existing models with expanded datasets suggests that expanded models could enhance existing risk adjustment and predictive models. Unfortunately, health insurers cannot use these techniques to reward good customers in the same way that is possible in life and property casualty insurance. Nevertheless there is, as a result of the new underwriting rules promulgated under the ACA, an increased need for population health management, and it is only a matter of time before predictive modeling becomes mainstream in healthcare, as risk adjustment already is.