SOCIETY OF ACTUARIES
PRODUCT DEVELOPMENT SECTION

ISSUE 110 • JUNE 2018

Product Matters!

Product Trends Around the World

By Elena Tonkovski and Joshua Dobiac
Page 4

Product Matters!

Issue 110 • June 2018

Published three times a year by the Product Development Section of the Society of Actuaries.

475 N. Martingale Road, Suite 600
Schaumburg, Ill 60173-2226
Phone: 847-706-3500 Fax: 847-706-3599
www.soa.org

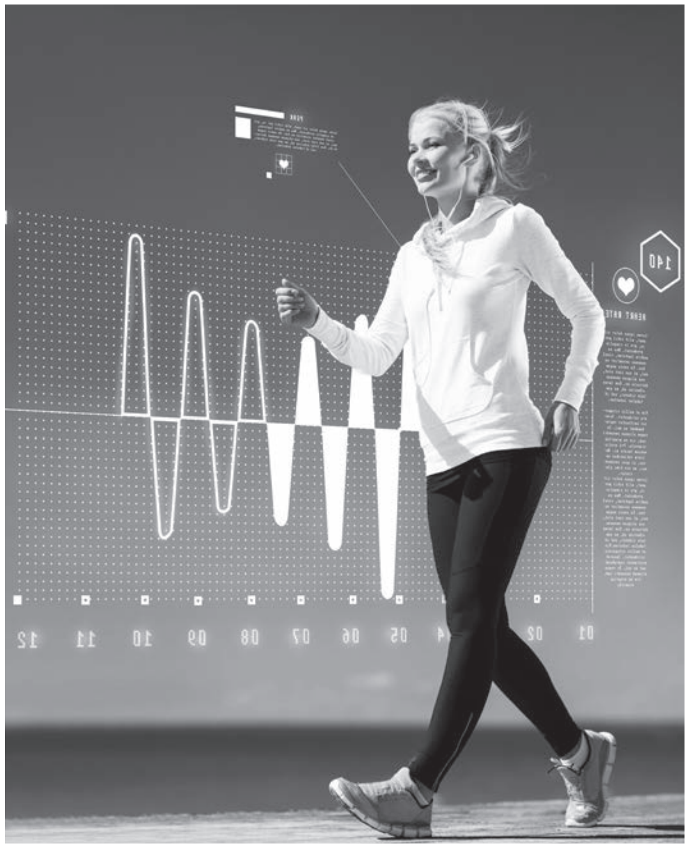
This newsletter is free to section members. Current issues are available on the SOA website (www.soa.org).

To join the section, SOA members and non-members can locate a membership form on the Product Development Section Web page at www.soa.org/productdevelopment.

Publication Schedule
Publication Month: October 2018
Articles Due: June 26, 2018

Chairperson's Corner

By Brock Robbins



Customer engagement is a dominant theme within the life insurance industry today. To stay connected, some insurers are beginning to promote and reward healthy choices through innovative product design.

This is an exciting movement because it expands the life insurance value proposition from death benefits to include broader lifestyle benefits. Products that reward policyholders for healthy choices (captured on cell phones and wearable devices) are a path to sustainable customer engagement. Moreover, it presents an opportunity to influence attitudes and change behavior.

Wellness and insurance is a win-win: Policyholders get healthier and life insurers get a better performing book of business.

In this issue of *Product Matters!*, Jennie McGinnis updates section members on the new In-force Management Subgroup. I expect we'll be hearing much more about this topic in the months ahead.

We also feature several other timely and high-interest topics, including

- Product Trends Around the World
- SOA Section Research
- Summary of Term Survey
- Shared Value
- Tax Reform on Life Pricing
- Continuation of PM for Life Insurance

As always, many thanks to our contributing authors. We greatly appreciate your time, efforts and expertise.

We welcome feedback from readers as well as any suggestions for future articles. ■

Brock Robbins, FSA, is deputy CEO of SCOR Global Life in the Americas. He can be reached at *brobbins@scor.com*.

Product Trends Around the World

By Elena Tonkovski and Joshua Dobiac

2017 was another year filled with innovation in the life and health insurance industry around the globe. The world around us keeps changing and changing F.A.S.T. propelling companies to respond with F.R.E.S.H. solutions! The F.A.S.T. changes are:

Financial: The world is more interconnected than ever before. While frictional challenges still exist in international banking and insurance, the ease with which an individual can invest in foreign stocks, bonds, and currencies has increased rapidly over the last 20 years. This has created opportunities for insurers to explore more diverse hybrid investment/insurance offerings that provide more tailored solutions to potential policyholders. The success of many future products will be tied to how they leverage the greater connectedness in financial markets and how they link it with traditional insurance offerings.

Authoritative: Solvency II, New GAAP, IFRS 17, new U.S. Valuation Manual regulations, tax changes, and more are also bringing a whirlwind of change. Marrying these regulatory changes to the growing concerns around privacy and data protection reveals a profound shift in how insurance is not only sold, but managed. This presents increased risk, to be sure, but insurers who take a forward-thinking attitude towards these opportunities will be able to get ahead of the market and define what insurance looks like in the future.

Social: Population growth, lengthening life expectancies around the world, increasing employment, and shrinking family size are fundamentally redefining social dynamics. Thus, the needs of people at different points in their life cycle are changing. Products that may have made sense 50 years ago (or even 20 years ago) may be poorly suited to current requirements. Recognizing how social dynamics are changing insurance needs will be instrumental for growth and success in the near- and medium-term.

Technological: The world now has a population of over 7 billion people, almost half of whom access the internet and utilize mobile phones regularly. 2.3 billion of them regularly use social media, mostly on their mobile devices. Not only have the financial markets become more interconnected, but so have people and businesses. Social media has extended well beyond just posting selfies or giving likes; it has now integrated into sales and marketing platforms. Never before has there been such a low-cost, globally penetrating means to advertise and sell products and to receive near-instantaneous feedback. Customers' buying habits and expectations are further fueled by smartphone applications, wearables, chat-bots, and more.

So how should insurers respond? Here are some F.R.E.S.H. product ideas companies have engaged in:

Flexible: One of the most salient characteristics of generational changes is the rejection of the one-size-fits-all model. Younger generations crave flexibility while those entering retirement are healthier than any prior generation, allowing them to pursue a wide range of activities in their golden years. Insurers can help by providing more flexible options to increase cover, to allow for policy loans and to promote greater convertibility between products (such as going from term to permanent life). A menu-like approach to rider features to allow for changes across family members, across benefits, or across investment options, as well as the use of web tools for customizing coverage, are additional means to entice clients to purchase products tailored to their specific needs. Allianz1 in Italy is a great example of a very user-friendly customizable web tool that helps clients choose the amount and type of coverages they want from Allianz's 13 individual building blocks from P&C, life and health insurance lines. Premiums for all selected products are bundled into one monthly payment. Another interesting example of flexible insurance is Sanlam's Go Cover product offered in South Africa. It is an on-demand type of micro-insurance for accidental death that can be easily bought on your phone for any length of time between 1 to 30 days. It's especially useful for customers who are going on a trip, engaging in a hazardous sport, or who wish to provide cover for their temporary employees.

> [I]nsurers who take a forward-thinking attitude towards these opportunities will be able to get ahead of the market and define what insurance looks like in the future.

Rewarding: We have already seen the rise in wearable tech—the internet-of-things has created an explosion of activity and lifestyle tracking. While privacy concerns are still under consideration, there is a profound opportunity to leverage this technology in the insurance space. By rewarding activities, insurers can move to a more-involved, central role in lifestyle promotion and management. This can encourage persistency, help to improve claims experience, and foster greater customer loyalty. For example, Prudential Hong Kong is currently offering policyholders nutrigenomic testing, which uses a person's DNA to determine how their genes affect their nutritional needs. A dietary sensitivity profile is then delivered through a mobile application to customers to be used to help them improve their well-being. Similarly, AllLife in South Africa is offering an affordable life insurance product to anyone living with diabetes. Premiums fluctuate depending on annual HbA1c tests, thereby encouraging people to proactively manage their health. Not only are customers rewarded with lower premiums for achieving good results from their annual tests, but they are also penalized when results have worsened.

Essential: In general, insurance is often not regarded as a necessity until it is either too late or not an ideal time to purchase it. Products are increasingly customer-centered, targeting needs at different life stages like senior-care products for the elderly, mortgage and wealth protection for the middle-aged, and savings plans for young families and their children. Products are also targeting substandard or underserved customer segments through disease-specific covers or affordable microinsurance and bancassurance channels. Companies now offer services beyond paying claims, such as rehabilitation; nutritional and psychological therapies; pre-screening benefits; doctor's hotlines for consultation and more. Union Life in China, for example, has focused on the primary need of many retirees: having a place to live as long as they need through the purchase of an annuity. Combining aspects of an annuity with inflation protection and focusing on specific needs of retirees, Union Life is offering upscale apartments equipped with medical facilities, hospitals, recreational facilities and more. Sun Life in Malaysia is another interesting example. They offer a Shariah-compliant protection and savings product which also provides for your religious needs by guaranteeing someone will perform the Hajj on your behalf if you are physically or financially unable to do so. This product combines traditional insurance with additional Islam-specific protections that help to assuage meaningful concerns among Malaysian Muslims.

Streamlined: Customers no longer need to travel to the local insurance agency to purchase their coverage. Websites, mobile apps, and engaging communication platforms can allow customers to handle every aspect of the insurance process, from purchase to filing a claim, without ever having to travel anywhere or even talk with someone. Accelerated underwriting can obviate the traditional challenge in insurance whereby many people abandon applications if they discover they cannot get instant coverage. Leveraging predictive analytics, machine learning, and related algorithms/tools can also enable targeted cross-selling and up-selling; such tools also allow for improved robo-advisors, which in conjunction with remotely situated human advisors can allow for a more optimal and low-cost business model. And while it may sound like science fiction at this point, virtual reality (VR) may eventually be leveraged to engage customers and provide low-cost customer service. MetLife in India has, in fact, piloted a VR-based customer service platform available at selected branches. VR headsets are provided for use by customers to get instant access to experts, view their policy details, make service requests, and check the status of their claims, all interactively. Another innovative example to engage customers can be found in Brazil, where insurance can be bought from a vending machine. BB MAPFRE is offering simple multi-line insurance products through specially made vending machines that are available in supermarkets, subway stations, local stores and other locations that people frequent while commuting or running errands. The idea is to make it as easy and convenient as possible for otherwise busy people to get

coverage. Sometimes all that is needed is accessibility. If buying insurance was as easy as buying a Coke, how many more people would have coverage?

Holistic: While insurers are focusing more and more on specific needs, they should never lose sight of the customer as a complete individual. The goal must be to provide targeted services, either alone or in partnership, that offer a comprehensive insurance and savings/investment experience for customers. This may include a suite of products that will cover life and P&C; protection and savings; families and individuals; and coverage for both high-concern critical conditions and for other less critical conditions that may still impair quality of life. An example of a holistic product for young families can be found in Indonesia where Prudential is offering expectant parents a product called My Child—a comprehensive and flexible solution that provides protection benefits, investment options, as well as savings riders for your child's education years. This product can be bought before the child is born and protects the mother until childbirth, or it can be bought after the child is born. Once the child reaches a certain age, the cover will get automatically transferred in their name. Green Delta's Nibedita product in Bangladesh offers another holistic example exclusively for women. Besides the traditional accidental coverage areas, it provides trauma allowance in cases of rape, road bullying, robberies, and acid attacks, and extended coverage for loss or damage to household goods and personal effects due to natural disasters. To create a one-stop service solution platform, customers are also given access to a mobile app which allows them to purchase the correct insurance, save for education or retirement, dial an emergency hotline should they be in distress, and get women-specific assistance to ensure they achieve their goals and become more self-reliant.

CONCLUSION

It seems cliché to say, but the world is changing and changing rapidly. This is resulting in an explosion of innovation in insurance offerings in all parts of the world affecting all customer segments, and there will be more to come from existing players and new market entrants ready to bring in their new ideas to the marketplace. Rethinking how insurance can and should be sold as well as moving to a non-commodified view of insurance, where products become more bespoke, will help insurers get closer and more integrated with the lives of their customers and proactively help them achieve their goals. ■

Elena Tonkovski, FSA, is assistant vice president & actuary, Global Products at RGA International Corporation. She can be reached at *ETonkovski@rgare.com*.

Joshua Dobiac is a consultant with Milliman. He can be reached at *josh.dobiac@milliman.com*.

SOA Section Research

By Jim Filmore

As you likely already know, the various sections of the Society of Actuaries (SOA) initiate research that is either conducted by working groups of the SOA or is bid out to external researchers. The sponsoring SOA sections provide funding as needed for the research and also provide oversight for the research through Project Oversight Groups (POGs).

Personally, I believe that such research is an important function of the SOA and the sections. Participating in such research projects is a way for actuaries to broaden their experience, meet other actuaries interested in similar topics, and to help give back to our profession.

Participating in research can take many forms:

1. You can suggest topics for research. That is a very simple way of being involved, but it is important. Your suggestion can turn into the next great piece of research that is produced by the SOA.

2. You can volunteer to be on a POG for research that is about to be initiated by the SOA.

3. Your company can bid on a research project where your team could be compensated for conducting the research.

For the last few years, Donna Megregian and I have had the opportunity to be the co-leads for research for the Product Development Section. It has been a pleasure working with a section that has such engaged members. During that time, we have promulgated research which started with ideas that now have become research reports with relevant and actionable information. Those research projects include topics such as Term Conversions, 2014VBT/2017CSO Impact Study, Impact of VM-20 on Life Insurance Product Development, Survey of Waiver of Premium Riders, and Understanding the Product Development Process, as well as many others. All of these reports are accessible under the research tab on the Product Development Section webpage (*soa.org/productdevelopment*).

I'd like to ask you to help us create the next great research report for our Product Development Section constituents. To do that, we want to hear your ideas, including issues and challenges that you face in your actuarial work, where research could help to provide useful insights.

Please email Donna Megregian (*DMegregian@RGARe.com*) and myself (*JFilmore@MunichRe.com*) with your ideas for research. You are also welcome to let us know if you are available to serve on a POG for future research projects. A list of those current opportunities can be found at *engage.soa.org/volunteeropportunities*. The commitment to participate on most POGs is fairly light and typically involves a one-hour conference call each month along with review of the initial project scope and final draft report created by the researcher. Some projects last only a few months while more in depth research projects (such as experience studies) may last 18 months. I've never regretted volunteering to be on a POG and I anticipate that you will have a similar experience. Being part of a POG gives you the ability to shape the project and be informed early as to the results.

Thank you! ■

Jim Filmore, FSA, MAAA, is vice president & actuary at MunichRe. He can be reached at *JFilmore@MunichRe.com*.

Term Life Insurance Market Update

By Susan J. Saip

In 2017, Milliman conducted a new broad-based survey on term life insurance, capturing historical data for key industry competitors, as well as company perspectives on a range of issues pertaining to these products into the future. Nearly all U.S. life insurance companies offer these products and are impacted by regulatory changes requiring compliance in the next few years (e.g., principle-based reserves and the 2017 Commissioners Standard Ordinary mortality table). The survey is structured similar to Milliman's annual universal life/indexed universal life study covering product and actuarial issues such as sales, profit measures, target surplus, reserves, risk management, underwriting, product design, compensation, and pricing. Forty carriers submitted responses.

In this article, a summary is presented of the trends in the U.S. individual term life insurance marketplace as revealed by survey responses.

TERM SALES

The graph in Figure 1 illustrates the level premium term period mix for return of premium (ROP) term as reported by survey participants from calendar years 2013 through 2016. Of the 40 survey participants, 13 reported ROP term sales. ROP term sales as a percent of total term sales were 3.6 percent in 2013 and 2014, decreasing to 3.4 percent in 2015, and increasing to 3.9 percent in 2016. ROP term sales were reported for 15-, 20-, 25-, and 30-year level premium term periods, with the majority of sales in the 20- and 30-year terms. The market share for the 30-year term increased year over year for the survey period, at the expense of the 15- and 20-year term.

All 40 survey participants reported non-ROP term sales. Non-ROP term sales as a percent of total term sales were 96.4 percent in 2013 and 2014, slightly increasing to 96.6 percent in 2015, and slightly decreasing to 96.1 percent in 2016. Non-ROP term sales were reported for yearly renewable term (YRT), 5-, 10-, 15-, 20-, 25-, and 30-year level premium term periods, as well as some sales in other level premium term periods. The graph in Figure 2 illustrates the non-ROP term mix by level premium term period as reported by survey participants from 2013 through 2016. The market share by level premium term period was fairly stable for non-ROP term products over the survey period. The market share primarily shifted from the 5-year term (-2.1 percent) to the 10-year term (+2.8 percent).

PROFIT MEASURES

The predominant profit measure reported by survey participants relative to the pricing of new term sales issued today is an after-tax, after-capital statutory return on investment/internal rate of return (ROI/IRR). The average ROI/IRR target reported by survey participants was 8.9 percent for ROP term products and 9.9 percent for non-ROP term. Profit margin is also a popular profit metric used by survey participants for term insurance. The average profit margin is 6.7 percent for ROP term and 4.5 percent for non-ROP term products.

Figure 3 (page 12) shows the percentage of survey participants reporting that they fell short of, met, or exceeded their profit goals separately for ROP term and non-ROP term products for calendar year 2016. Of note is that none of the participants fell short of their profit goals for ROP term products. The primary reasons reported for not meeting profit goals in 2016 were low interest earnings and higher than targeted expenses.

PRINCIPLE-BASED RESERVES AND THE 2017 CSO

Implementation of principle-based reserves (PBR) in accordance with the Valuation Manual Chapter 20 (VM-20) was allowed as early as Jan. 1, 2017, subject to a three-year transition period. Five of the 40 participants intended to implement PBR in calendar year 2017. The majority of survey participants (20) plan

Figure 1
Level Premium Term Period Mix by Year—ROP Term

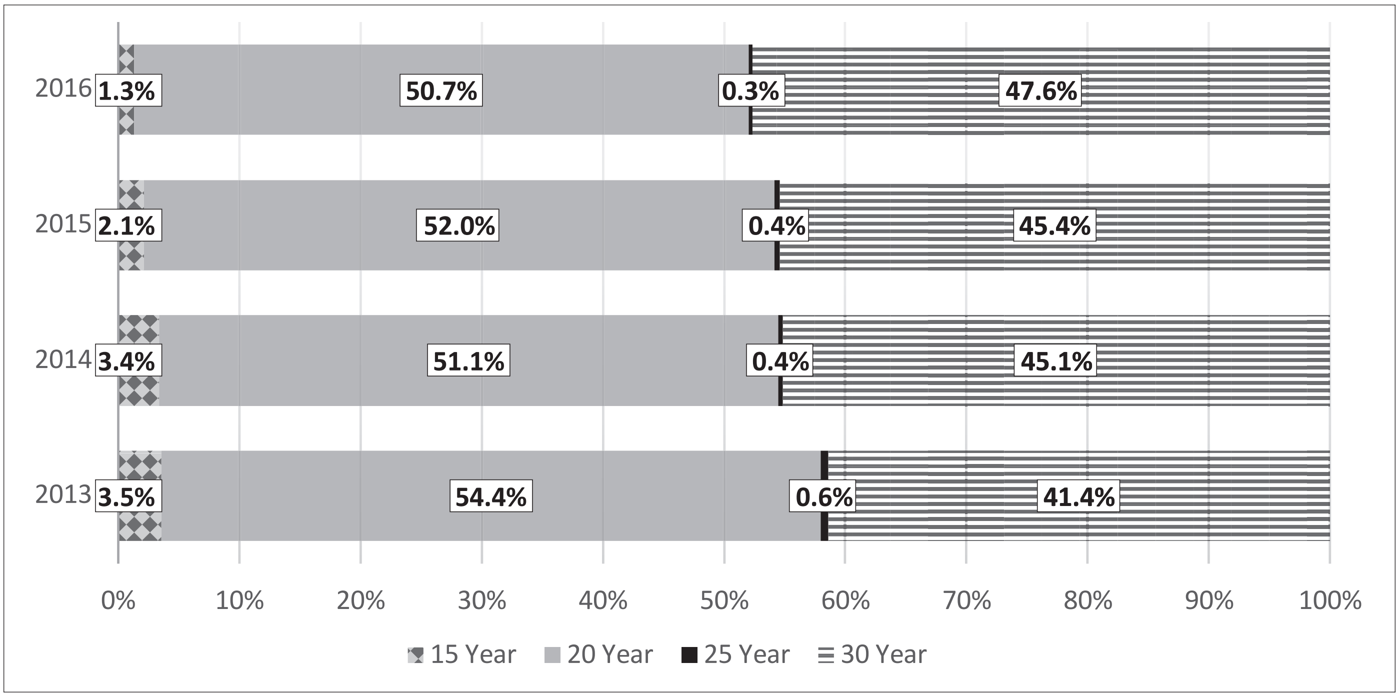


Figure 2
Level Premium Term Period Mix by Year—Non-ROP Term

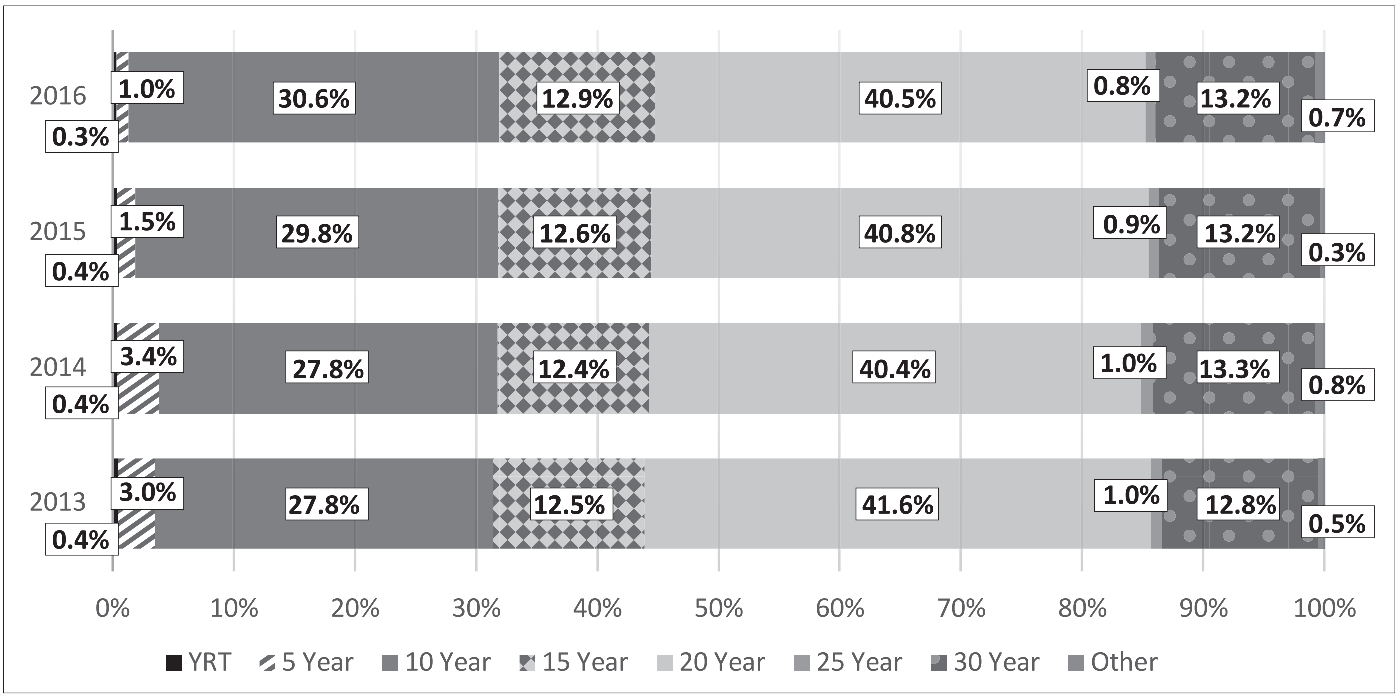
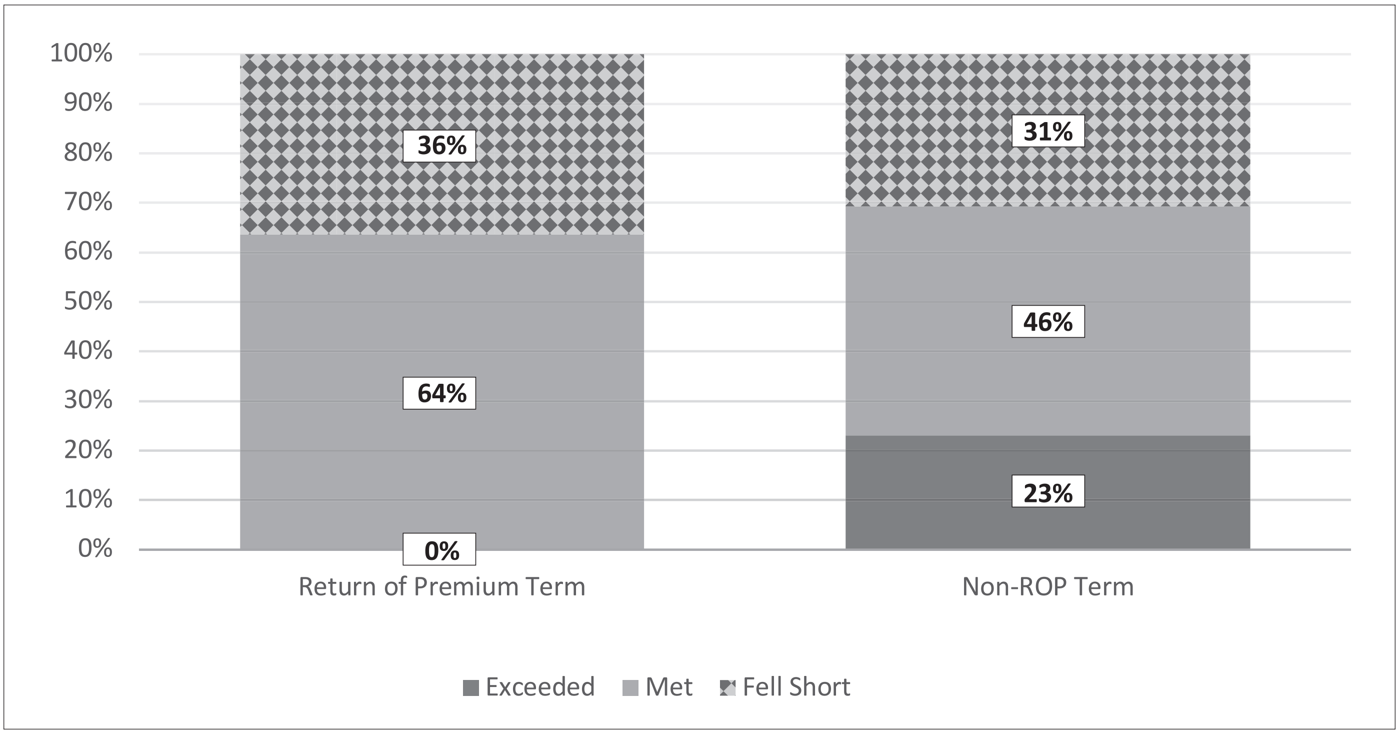


Figure 3
Actual Results Relative to Profit Goals for 2016



to implement PBR spread over the three-year phase-in period allowed. Three additional participants will implement PBR on Jan. 1, 2020 (the latest date allowed for implementation). Nine participants reported that the timing of PBR implementation is product dependent. The final three participants reported that they are using the small company exemption and are not implementing PBR. Factors impacting the rationale for participants' implementation plans include resource issues, lack of clarity regarding tax reserves, time needed, financial impact/cost/benefits, competitive reasons, awaiting the adoption of PBR by New York, and the advantages of continuing to use Actuarial Guideline 48.

Twenty-eight of the 40 survey participants reported the number of mortality segments being considered in light of VM-20 requirements. As indicated in VM-20, credibility may be determined at either the mortality segment level or at a more aggregate level if the mortality for the sub-classes (mortality segments) was determined using an aggregate level of mortality experience. The Valuation Manual defines a mortality segment as a subset of policies for which a separate mortality table representing the prudent estimate mortality assumption will be determined. Given the newness of these concepts, survey responders may have varied interpretations of the meaning of mortality segment. The number of segments ranged from one to 120, with an average of 12 and median of five. The most common composition for mortality segments reported by survey participants included only term products, followed by segments whose composition includes term products and universal life (UL) products.

Thirty participants provided a rating of how effective they believe PBR will be in making reserve financing arrangements (e.g., captives) for term insurance obsolete. Ratings are shown in the table in Figure 4. One participant reported that the effectiveness ranges from ineffective to average, therefore 31 responses are shown in the chart. More participants believe PBR will be effective rather than ineffective in making reserve financing arrangements obsolete. Note that this question was part of this term survey, and the responses may not be relevant to other products.

Figure 4
Effectiveness Ratings of PBR Making Reserve Financing Arrangements Obsolete

Rating	# of Responses
Very Ineffective	None
Ineffective	5
Average	12
Effective	14
Very Effective	none

Figure 5
Overall Level of Mortality—Aggregate

Aggregate Mortality Rates Were:	# of Participants		
	2014	2015	2016
Close to expected	16	16	14
Lower than expected	10	13	12
Greater than expected	7	4	7

Similar to PBR, the earliest effective date for the use of the 2017 Commissioner's Standard Ordinary (CSO) mortality table was Jan. 1, 2017, also subject to a three-year phase-in period. Fourteen survey participants reported that they would implement the 2017 CSO spread over the three-year period allowed. Twelve participants intended to implement the 2017 CSO in 2017. The remaining participants noted that implementation would be product-dependent.

UNDERWRITING

Of the 39 responses, simplified issue underwriting is being used by 18 participants on some plans, accelerated underwriting by 17 participants, and full underwriting by 38 participants.

The use of predictive modeling in the life insurance industry is becoming more common. Statistical models are utilized in predictive modeling relating outcomes/events to various risk factors/predictors. Scoring models are an example of predictive modeling used relative to life underwriting. Scoring models are being used by 18 survey participants to underwrite their term policies. Nine of the 18 use purely external scoring models and five additional participants use purely internal scoring models. The remaining four participants reported they use both internal and external scoring models. Eleven of the 18 participants reported using scoring models with automated rules. In total, six participants use lab scoring models, 10 use credit scoring models, 11 use scoring models relative to motor vehicle records, and 14 use prescription history scoring models.

PRICING

The overall level of mortality experienced on term insurance relative to that assumed in pricing was reported by survey participants. Figure 5 shows the aggregate mortality levels that were reported by 33 participants for calendar years 2014, 2015, and 2016. The percentage of participants that reported mortality rates were close to or lower than those assumed in pricing was 79 percent in 2014, 88 percent in 2015, and 79 percent in 2016. Note that of the 33 participants reporting aggregate mortality levels, 20 included experience after the level term period.

Similarly, the overall level of lapses experienced on term insurance relative to that assumed in pricing was reported by survey participants. Aggregate lapse rates were reported for calendar years 2014, 2015, and 2016. Actual lapse experience on an aggregate basis was close to or lower than that assumed in pricing for 91 percent of participants in 2014, 90 percent in 2015, and 92 percent in 2016.

CONCLUSION

These are interesting times in the term life insurance marketplace. Carriers are dealing with significant regulatory changes, such as PBR and the 2017 CSO. Innovations in underwriting are emerging, such as new underwriting approaches (e.g., accelerated underwriting) and the use of predictive modeling. These recent changes are having a more significant impact on the term life insurance market than has been seen for some time. It is imperative for term writers to stay abreast of these issues and opportunities.

A complimentary copy of the executive summary of the January 2018 Term Life Insurance Issues report may be found at: *http://www.milliman.com/insight/2018/Term-life-insurance-issues/*. ■

Sue Saip, FSA, MAAA, is a consulting actuary at Milliman. She can be reached at *sue.saip@milliman.com*.

Shared Value Insurance: Award Winning Innovation

By Alan Pollard and Benny Rubin

Shared-value insurance has emerged as a new category of insurance and is capturing a large number of industry innovation awards both in the USA and internationally. The concept of "shared value" was first introduced by Michael Porter and Mark Kramer in their seminal work in the *Harvard Business Review*. They formally define it as "a framework of framing policies and operating practices in such a way that enhances the competitiveness of a company while simultaneously advancing the economic and social condition in the communities in which it operates." The framework puts an equal weighting on creating economic value and addressing societal needs and challenges. It operationalizes this philosophy by identifying and expanding connections between societal and economic progress. Shared value can also be expressed as a type of management strategy where a business aligns its objectives with success of all its stakeholders.

Kramer and Porter argue that is imperative to embrace a shared value approach for long-term growth in a world where the role of business in society is changing due to increasingly liberal societal trends and consumer-centric regulatory reform.

While many (if not all) sectors can benefit from a shift in mindset towards a shared-value approach, the insurance industry is uniquely positioned to take a significant advantage from this proposition.

HOW INSURERS ARE UNIQUELY POSITIONED TO BENEFIT FROM A SHARED VALUE APPROACH

The insurance industry's primary function is to protect individuals and organizations against the financial risk arising from the occurrence of adverse events. When an insured adverse event occurs, the insurer is contractually obligated to pay the resultant claim (i.e., the insurance industry monetizes risks). Insurance companies suffer when adverse events occur more frequently or more severely than expected and benefit from the opposite. It follows that when societal conditions improve, such as with a reduction of the disease burden, a decline in the frequency of accidents, and general improvements in societal wellbeing, the industry becomes more profitable and/or more competitive. In fact, it is likely that the only other stakeholder with such a direct economic interest in such improvements is government.

Porter argues that "insurance is the ultimate shared value industry, where social impact is integral to economic success." However, most insurers remain rooted in the passive actuarial model of upfront risk selection and pricing followed by claims mitigation. Insurers benefit more than almost any other industry from societal advances (in health care and in health awareness in particular) but lag behind in proactively tackling the societal conditions that will most affect their business. Insurers to date have largely and somewhat surprisingly overlooked opportunities to enhance outcomes for their customers, society and ultimately, for themselves.

THE CHANGING NATURE OF RISK, THE HEALTH CARE PARADOX AND THE POWER OF INCENTIVES

The Changing Nature of Risk

It is now widely understood that lifestyle factors play a significant role in the modern disease and mortality burdens. The Oxford Health Alliance termed a useful phrase of 4-4-60 to help aid this understanding—four lifestyle behavior factors (physical inactivity, poor diet, tobacco use, and excess alcohol intake) are associated with four chronic diseases (cardiovascular disease, diabetes, chronic lung disease, and various cancers) that contribute to 60 percent of deaths worldwide (see Figure 1).

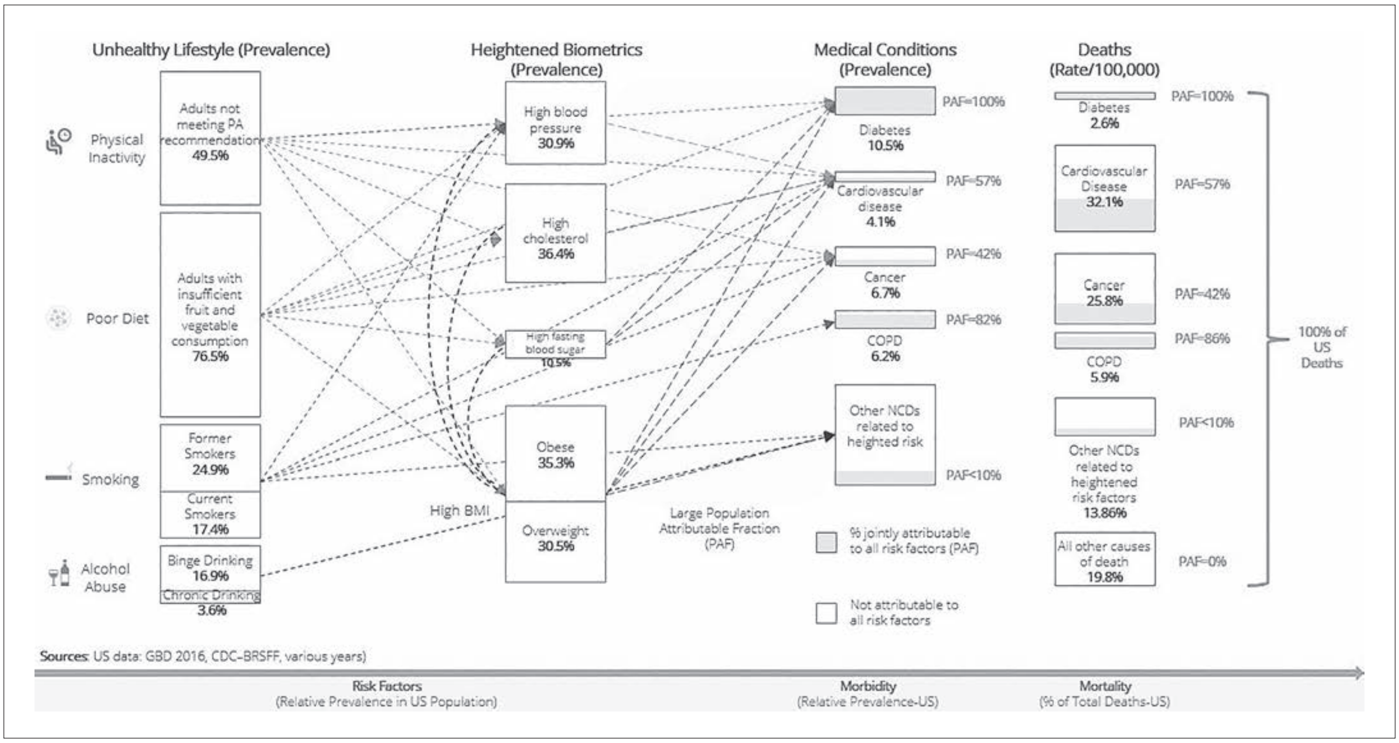
The Health Care Paradox

Yet with all this understanding most societies perpetuate the paradox of over-consuming health care but under-consuming prevention. Health systems are known to spend as little as 2 percent of health expenditure on preventive and lifestyle related services despite the oversized role these play on the disease burden.

The individual consumer similarly falls victim to this. In consuming health care services, the cost of health care is often hidden (paid by insurer or national health) while many of the benefits are immediate, leading to over-consumption. With prevention, the cost is evident (time taken to excersize or restraint required to avoid that slice of cake) however the benefits only materialize in the future—leading to under-consumption.

The trade-off of instant gratification over long-term wellness, coupled with the fact that people are irrationally over-optimistic about their abilities to overcome health issues, means that people tend to make poor and short-sighted decisions when it comes to their health.

Figure 1
Mortality Drivers



Behavior Change through Nudges

Despite the difficulties noted above it has been shown that short-term nudges in the form of incentives and appropriate messaging have been effective drivers of behavior change.

APPLICATION OF THE SHARED-VALUE MODEL TO INSURANCE

We've established that an insurer can generate risk savings if its clients improve their health. We've also seen that clients can improve their health by making healthier lifestyle choices though they typically tend not to as explained by a variety of behavioral economic theories. Yet certain tools have been shown to be effective in driving healthy behavioral change.

If the insurer can facilitate the improvement of its clients' health, the portion of the subsequent insurance savings can be used to provide incentives that encourage clients to make healthier choices, so fuelling a virtuous cycle of value creation and health improvement. This is the essence of the shared value insurance model: addressing the shortcomings of human behavior and insurance design, and integrating the two into a powerful form of insurance that actively promotes health improvement.

Shared value's application to insurance was pioneered by Discovery, a South African financial services group. Discovery conceived this new category of shared value insurance with its innovative business model, Vitality. Vitality aims to improve health outcomes through behavior-change incentives that are focused on health promotion. The business model simultaneously provides material benefits to Discovery, its clients, and society as a whole. Vitality is now partnered with a network of leading global insurers who use the model in their markets to transform their insurance offerings, and the health of their clients.

HOW VITALITY WORKS

Members of the Vitality program are awarded Vitality points over the course of the year, based on the wellness activities they complete, which include increasing physical activity, purchasing healthy foods, assessing their health profile, having appropriate preventive screenings and more. These points-earning activities are designed to tackle the lifestyle factors discussed above, and are aligned to the impact that completing that activity will have on health outcomes. Vitality points aggregate towards a Vitality status. The higher the status the higher the level of rewards—such as substantial discounts at retail and travel partners. These rewards and discounts are funded through the enhanced insurance savings that result from the client's improved risk profile. But perhaps most meaningfully there is also a direct insurance advantage—clients can lower their insurance contributions through demonstrating positive lifestyle behaviors. Instead of underwriting the policyholder at a single point in time and locking in a rate forever, the insurer now has the opportunity of continual engagement with the policyholder and getting up to date insights on the underlying risks they are covering. In many of the markets in which Vitality operates, the insurer gives the policyholder an upfront "benefit of the doubt" that they will engage in healthy behaviors. This results in a competitive advantage of up to 15 percent of premium. If the policyholder doesn't demonstrate healthy behaviors their premium will adjust upwards over time.

The Dynamic Pricing Model

The model in Figure 2 leverages the behavioral economics principles of nudges and incentives, personalized technologies including wearables and smartwatches, and data analytics to facilitate incremental positive changes in lifestyle and health behaviors. The model has been shown to lower morbidity and mortality rates, and consequently the cost of claims. A portion of this actuarial surplus is recursively channelled back to clients in the form of rewards and dynamic premium pricing.

The Vitality Shared Value Model

The Vitality Shared Value Insurance model in Figure 3 not only creates a virtuous cycle of value-creation, it depends on it for its own sustainability. The value that is created and subsequently shared is not confined to the insurance environment. The network of reward and retail partners is critical to the success of the model and these partners share in the value creation through increased revenue, improved customer loyalty and exposure to a broader customer base.

IMPACT OF THE MODEL

Framing insurance in the shared value construct transforms a traditional grudge purchase into a driving force for societal change. *The Guardian* describes this transformation as an example of a business "grabbing hold of a social issue that is at the core of their business, and figuring out how to wrap that into their strategy

Figure 2
Dynamic Pricing Model

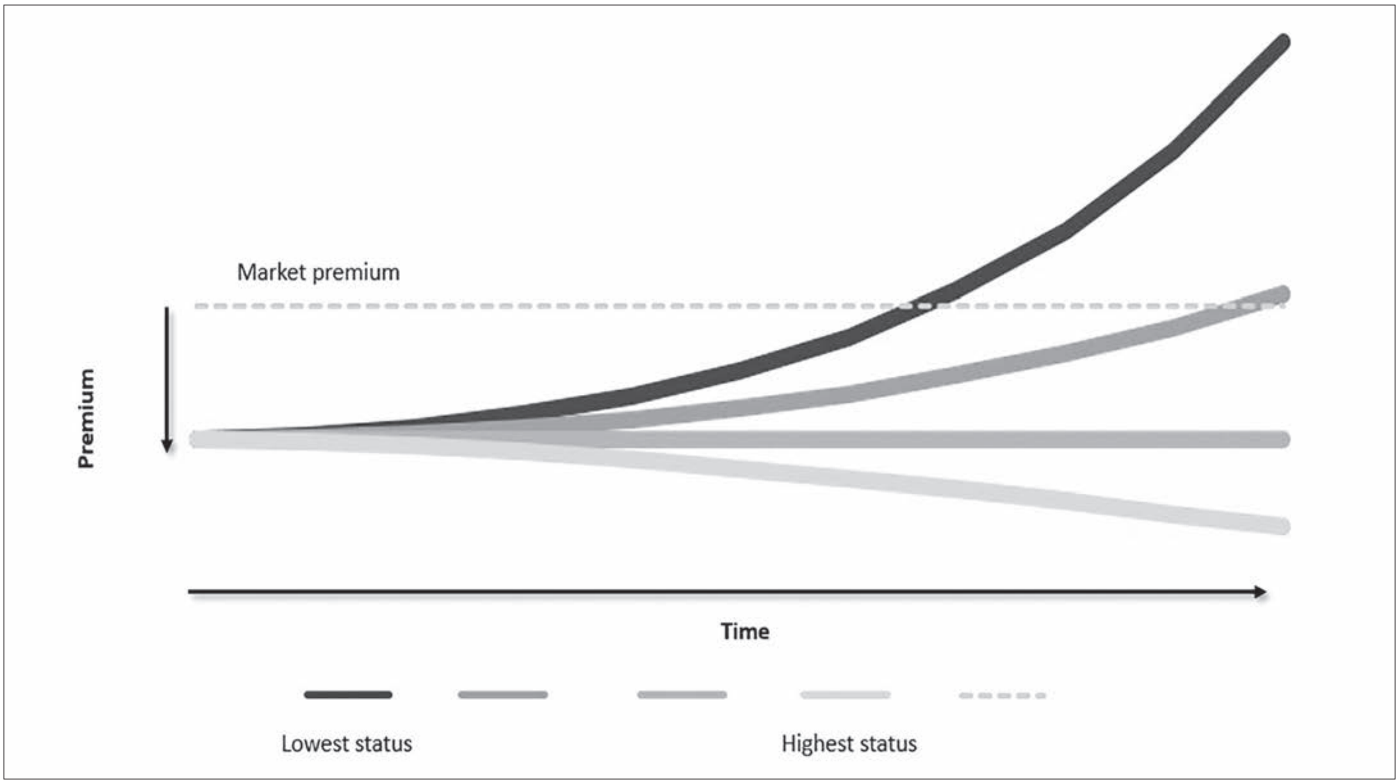


Figure 3
Vitality Shared Value Model

and operations."[1] After capturing a large proportion of South Africa's private health insurance market, Discovery introduced behavioral incentives to motor and life insurance clients, creating synergies across these lines by integrating Vitality, and thereby reducing car accidents and lowering medical and life claims.

Discovery's success in South Africa has led to the development of the Global Vitality Network, an alliance of powerful global insurers: AIA (Asia), Ping An (China), Generali (Europe), Sumitomo (Japan), John Hancock (U.S.), Manulife (Canada), Vitality Life & Health (U.K., previously a Prudential and Discovery JV), and Discovery (South Africa). It now operates in 16 countries.

The insurance industry holds a vital role in local systems and is uniquely positioned to monetize better societal outcomes. The opportunity to use this powerful force for good is a refreshing proposition in the context of an often stagnant industry. A shared value mind-set aligns the health of members, the bottom line of insurers and the wellbeing of society. ■

Alan Pollard is a Fellow of the Actuarial Society of South Africa and the Institute of Actuaries. He currently serves as President, Global Product and Innovation for Vitality Group and serves on the Board of Directors and Executive Committee of Discovery. He can be reached at *alan.pollard@vitalitygroup.com*.

Benny Rubin is an actuarial analyst at Discovery. He is involved in the roll-out of shared value Vitality products to Discovery's global insurance partners. He can be reached at *benny.rubin@vitalitygroup.com*.

ENDNOTES

1 *Strategy and Society: The Link Between Competitive Advantage and Corporate Social Responsibility* by Prof Michael E. Porter and Mark R. Kramer.

2 *https://www.theguardian.com/sustainable-business/blog/creating-shared-value-social-progress-profit*

Introducing the In-Force Management Subgroup

By Jennie McGinnis

While companies have managed their in-force for some time, there is a more recent and ongoing trend to dedicate resources—people, time and money—to such activities. As the count of organizations with teams dedicated to these activities rises, so increases the number of individuals who identify as specializing in in-force management.

Likewise, while the SOA has offered professional development and education on in-force management topics for some time, the availability of such sessions and webcasts has also grown. Recognizing the potential for more dedicated support to those practicing in-force management, discussions began about a year and a half ago regarding what form such dedicated support might take.

There were many considerations along the way. How formal should the group be? The activities covered can be pretty expansive and touch nearly every section's mission—where would this actually "fit"? Will people actually be interested in participating?

Fast-forward a year, to January 2018, when the Product Development Section Council approved the formation of a subgroup on in-force management. The purpose of this group is to advance the practice of in-force management through the fostering and promotion of networking among professionals, facilitation of continuing education, and support of research opportunities.

FOSTER AND PROMOTE NETWORKING AMONG PROFESSIONALS

Our key channel of communication is a listserv, which can be accessed via the SOA's website.[1]

While listserv members can interact at any time via the group's email address, more formal messages are scheduled for about once a month. Many are expected to have an interactive element, seeking input and feedback on what topics and methods of connecting most resonate with members' preferences.

This summer we'll be hosting our first town hall, which is similar to a webcast but with more active attendee participation. Work is also underway to enable those who are attending the SOA Annual Meeting & Exhibit to interact and network in person during Monday's lunch. This will be co-sponsored with the Joint Risk Management Section, an early indication of how the subgroup will be able to work across the SOA though formally associated with one section.

FACILITATE CONTINUING EDUCATION

A number of sessions related to in-force management have been held and are planned for the year.

At the Life Insurance Conference, held in Chicago in April, sessions included "Life Insurance In-Force Management" and "Rock and a Hard Place: The Decision to Increase COIs."

Then, in Baltimore in May at the Life & Annuity Symposium, sessions included "In-force Management: Getting More from What You Have" and "Managing, Valuing, and Reporting Non-Guaranteed Elements." The subgroup's activities were also highlighted during the section's breakfast.

Sessions for the Valuation Actuary Symposium and the 2018 Annual Meeting & Exhibit are in the works, and there are also plans to host a webcast toward the end of the year.

SUPPORT RESEARCH OPPORTUNITIES

While we don't have immediate plans to fund research, we are certainly keen to facilitate the sharing of knowledge in and amongst the group. To this end, in addition to the avenues outlined above, you can expect to continue to see in-force management content in future issues of *Product Matters!*.

ONGOING SUPPORT

All of the above can only take place through the assistance of volunteers. While we're in the process of establishing a formal leadership team, we've had a number of individuals step up to ensure our inaugural year runs to plan.

If you have a particular interest—whether it be presenting, writing, planning, or otherwise—please contact me. Keep in mind that those interested in volunteering as subgroup leadership must be members of both the SOA and Product Development Section.

With more than 250 individuals having already joined this subgroup, the future of the group looks quite positive. We hope you'll join us! ■

Jennie McGinnis, FSA, CERA, MAAA, is the leader of the In-Force Management Subgroup and senior vice president & in-force portfolio manager at Swiss Re. She can be reached at *Jennifer_McGinnis@swissre.com*.

ENDNOTES

1 Go to *https://www.soa.org/News-and-Publications/Listservs/list-public-listservs.aspx*, find "In-Force Management Listserv" and JOIN.

Tax Reform Impacts on Life Insurance Pricing and Profitability

By Curt Clingerman, Paul Fedchak, Casey Malone, and Craig Reynolds

On Dec. 22, 2017, President Trump signed the Tax Cuts and Jobs Act (Tax Reform) into law. While the impacts of the new tax law on the broader economy remain to be seen, projecting the impact on life and annuity profitability is something we can approximate right now. Tax Reform will either lead to changes in projected profitability, changes in product design or pricing, or both. In order to understand the possible approximate impact of the changes to the tax code, we prepared this analysis to measure the impact on a range of different product types, including an illustrative plan of each of the following types:

- Current assumption universal life (CAUL)
- Par whole life (WL)
- Term under Valuation Manual Chapter 20 (VM-20) (TermVM20)
- Term under peak statutory (XXX) and Actuarial Guideline (AG) 48 (TermAG48)
- Indexed universal life (IUL)
- Fixed indexed annuity (FIA)

The actual impact of Tax Reform will vary with the facts and circumstances of the case at hand, including the product design and the tax situation of the company. However, we can still gain some value from looking at an illustrative case.

For this purpose, we considered three key changes in the tax law affecting life insurers, as well as a fourth change, which remains an open issue:

1. An extension of the proxy deferred acquisition cost (DAC) tax amortization period from 10 years to 15 years and an increase in the proxy DAC tax rate—from 7.7 percent to 9.2 percent for non-group life insurance and from 1.75 percent to 2.09 percent for annuities.
2. A change in the way the tax reserves are calculated via the application of a 92.81 percent scalar to statutory reserves excluding deficiency reserves, subject to a cash value floor. This implies a simplifying assumption that the CRVM tax reserve basis after tax reform equals the statutory reserve basis prior to tax reform.
3. A reduction in the federal income tax rate from 35 percent to 21 percent.
4. The risk-based capital (RBC) factors were increased by a scalar multiple of (1 - 0.21) / (1 - 0.35) to reflect the lower tax rate. We present this as a separate step because, as of this writing, the National Association of Insurance Commissioners (NAIC) has not provided guidance. It is possible that the NAIC will adjust the gross RBC factors instead, so that the after-tax factors remain unchanged.[1]

Of these, the tax rate change will tend to increase after-tax profits, while the other factors will generally decrease after-tax profits. For most of our illustrative product types, the tax rate change modestly dominates the other changes, though the impact varies with product type and funding level, as demonstrated in the CAUL example.

The table in Figure 1 shows a summary of Tax Reform impact to internal rate of return (IRR) and profit margin, assuming no change in product design, pricing, or premium levels. All profit metrics are after tax and cost of capital. Profit margin calculation uses a level discount rate of 5 percent.

Figure 1
Summary of Illustrative Tax Reform Profitability Impacts After Tax and Cost of Capital

	Before Tax Reform		After Tax Reform	
	IRR	Profit Margin	IRR	Profit Margin
CAUL	15.2%	6.3%	15.4%	7.9%
WL	10.0%	2.7%	8.8%	2.1%
TermVM20	9.6%	5.1%	9.8%	6.5%
TermAG48	26.5%	9.5%	8.7%	3.6%
IUL	10.0%	5.2%	10.0%	6.4%
FIA	10.2%	5.9%	10.0%	7.4%

In the following sections, we provide stepwise detail on each example, including illustrative product adjustments to return to the original profitability level.

CURRENT ASSUMPTION UNIVERSAL LIFE

Our illustrative CAUL product is a profitable back-loaded plan with statutory and tax reserves before the change assumed to equal the average of the account value and the cash surrender value—the "California" method. Products with higher tax reserves than this would benefit less from tax reform than is illustrated here.

First, let us look by step at the impact on profits after tax and cost of capital, as the tax code changes are layered on. Composite results reflect a variety of different ages, underwriting classes, and premium paying patterns as shown in Figure 2.

Figure 2
CAUL Composite Profit Results

	IRR	Profit Margin
Before Tax Reform	15.2%	6.3%
Change DAC Tax	13.7%	5.9%
Change Tax Reserves	12.2%	5.6%
Change Tax Rate	17.1%	8.1%
Change RBC	15.4%	7.9%

We solved for a multiplier to apply to the initial COI table to return to the initial profit margin. The resulting multiplier is 92 percent.

The relative impact of the changes depends on the funding level of the contract. In our model, we include cells that are funded to be 20-year term, and whole life using single premium, 7-pay premium, and whole life premium on a current assumption basis. The table in Figure 3 shows the impact by funding level.

Figure 3
CAUL Tax Reform Impacts by Funding Level

	Before Tax Reform		After Tax Reform		Increase	
	IRR	Profit Margin	IRR	Profit Margin	IRR	Profit Margin
Single Pay	12.5%	5.3%	12.5%	6.6%	0.1%	1.3%
7-Pay	14.7%	6.2%	14.9%	7.9%	0.2%	1.7%
Level-Pay WL	16.9%	6.5%	17.2%	8.2%	0.3%	1.7%
20-Year Term	20.7%	9.2%	21.1%	11.3%	0.5%	2.1%

Varying impacts by funding level illustrate the importance of granular analysis of Tax Reform impacts, though it appears that Tax Reform is a net win for the company, or the policyholder, or both—at least as far as this illustrative CAUL policy is concerned.

PARTICIPATING WHOLE LIFE

Our whole life product has a 20-pay premium pattern. The illustrative example in Figure 4 is based on a model office containing a typical range of issue age, sex and risk class combinations. The product has a competitive dividend scale. Statutory reserves are calculated based on Commissioner's Reserve Valuation Method (CRVM) at 3.5 percent. Guaranteed cash values are based on an initial nonforfeiture rate of 4.5 percent. The table in Figure 4 shows the impact of various aspects of tax reform.

Figure 4
WL Composite Profit Results

	IRR	Profit Margin
Before Tax Reform	10.0%	3.4%
Change DAC Tax	9.3%	2.7%
Change Tax Reserves	6.9%	–0.2%
Change Tax Rate	9.1%	3.0%
Change RBC	8.9%	2.8%

For the product adjustment to whole life, we took a two-step approach. First we reduced the nonforfeiture interest rate to 4.0 percent, increasing guaranteed cash values. Increasing the guaranteed cash value helps to mute the impact of the tax reserve reduction. Second, we reduced the overall dividend scale by 8 percent.

The result is that the policyholder receives higher cash values, by as much as 10 percent, in the early policy years, before the initial and revised patterns ultimately converge toward the face amount. On the other hand, the overall death benefit is lower in the adjusted, post-reform product because the dividends purchase less in paid-up additions. It is worth noting that this situation could also result in illustration testing challenges, analysis of which is beyond the scope of this example.

TERM

We evaluated a 20-year level term product under both XXX reserve with AG48 reserve financing (AG48) and VM-20 reserve approaches. The AG48 approach assumes that XXX statutory reserves in excess of the AG48 primary security level will be ceded to a captive reinsurer and backed by a letter of credit. The direct company retains the full XXX tax reserve, which exceeds the AG48 primary security level. Retaining the full XXX tax reserve results in a large taxable loss, which can be used to offset taxable gains from other business. The magnitude of the resulting tax benefit depends on the tax situation of the company. Under VM-20, while not explicitly defined, the tax reserve was assumed to be the same as the statutory reserve, which in this example was predominantly the net premium reserve.

The post-level period was ignored for simplicity. The premiums under the AG48 financing approach are competitive with the top five to 10 companies in the market. Premiums under the VM-20 approach are approximately 10 percent higher than premiums under AG48. This results in profit measures under VM-20 in line with industry norms, but still below those under AG48. The table in Figure 5 shows the impact of the tax changes under VM-20.

Figure 5
TermVM20 Composite Profit Results

	IRR	Profit Margin
Before Tax Reform	9.6%	5.1%
Change DAC Tax	9.1%	4.8%
Change Tax Reserves	8.8%	4.6%
Change Tax Rate	10.1%	6.6%
Change RBC	9.8%	6.5%

Under VM-20, the impact of Tax Reform is relatively modest, but positive. In this example the company can decrease premiums by 3 percent while maintaining the profit margin before Tax Reform. Because our VM-20 premiums began 10 percent higher than the AG48 premiums, this would still be approximately 7 percent higher than premiums for a product designed under the AG48 approach before Tax Reform.

The table in Figure 6 shows the impact of the changes under AG48.

Figure 6
TermAG48 Composite Profit Results

	IRR	Profit Margin
Before Tax Reform	26.5%	9.5%
Change DAC Tax	25.7%	9.1%
Change Tax Reserves	22.4%	7.9%
Change Tax Rate	9.9%	4.0%
Change RBC	8.7%	3.6%

The Tax Reform changes significantly reduce the tax benefit recognized via the AG48 financing approach. In order to return to profit margin levels similar to those before Tax Reform, a 10 percent premium increase would be required. Alternatively, a company could increase premiums by approximately 3 percent while using AG48 financing and realize profits in line with the VM-20 approach, although still lower than AG48 profits before Tax Reform.

In other words, to equate the profitability under VM-20 before Tax Reform, VM-20 after Tax Reform, and AG48 after Tax Reform, there will only be a 4 percent premium difference. Whereas, before Tax Reform, the AG48 premium could be 10 percent lower while realizing higher profits. It is plausible that Tax Reform might push companies to move toward VM-20 reserving for term sooner than originally expected.

INDEXED UNIVERSAL LIFE

Our illustrative IUL cell assumes target premiums based on level premium payments to age 65 followed by moderate withdrawals from age 65 to 100. Cash value is sufficient to carry the policy to age 100. We have assumed a statutory reserve as the average of the account value and cash value. The table in Figure 7 shows the impact of various aspects of Tax Reform.

Figure 7
IUL Composite Profit Results

	IRR	Profit Margin
Before Tax Reform	10.0%	5.2%
Change DAC Tax	9.4%	4.8%
Change Tax Reserves	8.7%	4.5%
Change Tax Rate	10.2%	6.5%
Change RBC	10.0%	6.4%

The overall impact of Tax Reform is modest, but positive, for most of these illustrative product types. TermAG48 is the most significant exception.

The net impact of Tax Reform appears to be negligible on an IRR basis and a small net increase on a profit margin basis of 1.2 percent. Because the IRR before and after tax reform is the same, some companies in this situation may choose to keep pricing unchanged. However, if a company is willing to accept a lower IRR but return to its initial profit margin, its COI could be reduced by approximately 8 percent.

FIXED INDEXED ANNUITY

Our illustrative FIA product has a six-year surrender charge period with a maximum charge of 7 percent. It also contains a Guaranteed Minimum Withdrawal Benefit (GMWB) with an 8 percent rollup, capped at 200 percent of premium, and maximum withdrawal rates of 5 percent, 6 percent, and 7 percent at attained ages 60, 70, and 80, respectively. The pricing results reflect a combination of various issue ages.

The cumulative changes for the four changes in the tax law are shown in the table in Figure 8.

Figure 8
FIA Profit Results

	IRR	Profit Margin
Before Tax Reform	10.2%	5.9%
Change DAC Tax	10.1%	5.9%
Change Tax Reserves	8.8%	5.0%
Change Tax Rate	10.6%	7.5%
Change RBC	10.0%	7.4%

We solved for the increase in option budget after Tax Reform that would bring the profit margin in line with the initial results. The result was an increase in the option budget of 21 basis points.

The change in the proxy DAC tax is immaterial for FIA because the deferral rates remain small for annuities relative to life products. The decreased tax rate more than offsets the decrease in earnings, which is due to the change in tax reserves. For our illustrative FIA product, tax reform leads to either a 1.5 percent increase in profit margin to the company or an increase of 0.21 percent in the option budget for the consumer, or some combination of the two.

CONCLUSION

The overall impact of Tax Reform is modest, but positive, for most of these illustrative product types. TermAG48 is the most significant exception, where the tax leverage of reserve financing drops in value significantly. While the tax benefit of the rate drop is significant, this is largely offset by the RBC, DAC tax, and tax reserve changes. ■

Curt Clingerman, FSA, MAAA, is a consulting actuary at Milliman. He can be reached at *curt.clingerman@milliman.com*.

Paul Fedchak, FSA, MAAA, is a principal and consulting actuary at Milliman. He can be reached at *paul.fedchak@milliman.com*.

Casey Malone, FSA, MAAA, CERA, is a consulting actuary at Milliman. He can be reached at *casey.malone@milliman.com*.

Craig Reynolds, FSA, MAAA, is a principal and consulting actuary at Milliman. He can be reached at *craig.reynolds@milliman.com*.

ENDNOTES

1 Since this article was written, NAIC discussions have continued. As the article is going to press, it appears that C-1 and C-2 after-tax factors might increase, while C-3 and C-4 after-tax factors might remain the same. If this turns out to be true, the capital impact postulated here might be overstated.

Predictive Modeling for Life Insurance

Ways Life Insurers Can Participate in the Business Analytics Revolution

By Chris Stehno and Jim Guszcza
Contributors: Mike Batty, Arun Tripathi, Alice Kroll, Cheng-sheng Peter Wu, David Moore, and Mitch Katcher

Editor's Note: This article is part two of two. Part one was published in the February 2018 issue. It has been formatted for the newsletter and is reprinted with permission from Deloitte Development LLC.

BUILDING A PREDICTIVE MODEL

After discussing so much about what can be done with predictive models in life insurance, we have finally come to how to build one. The following section describes the technical process of developing a model.

Data

Predictive modeling is essentially an exercise in empirical data analysis. Modelers search through mountains of data for repeatable, statistically significant relationships with the target (underwriting decision in this case), and generate the algorithm that produces the best fit. Since it is central to the modeling process, the best place to begin the technical discussion is with the data.

Data miners prefer to start with a wide lens and filter out potential data sources as necessary. We start by asking, "What data can be obtained for an individual applicant?" And then move to questions such as, "Which data elements show a relationship with the target?," "Is the penetration of the data enough to generate statistical significance," "Is the correlation strong enough to justify the data's cost?," and finally, "Based upon regulatory and compliance concerns, can the data be included in a predictive model in the underwriting process?" In our experience, working through these questions leads to two different classes of data: a sub-selection of traditional underwriting requirements, and alternative datasets not traditionally used in underwriting assessments.

The traditional underwriting requirements incorporated into the predictive models generally meet several criteria:

- Available within the first one to two days after an application is submitted Transmitted electronically in a machine readable format
- Are typically ordered for all medically underwritten applicants
- Several of the most common data sources are discussed below. The actual sources used by any particular life insurer may vary.

Application Data (including part 2 or tele-interview)—any piece of data submitted to the company by an insurance applicant is a candidate for the predictive model. There are two keys to successfully using the data contained in an insurance application in a model. First, the questions which are easiest to work with are in a format such as multiple choice, Yes/No, or numerical. However, new text mining applications are making free form text possible in some situations. Second, the new business process should capture the application electronically and store the answers in a machine readable format such as a database. Life insurers who do not have application data in a compatible format face considerable manual data entry during model build.

MIB—When member companies receive an application, they will request a report from the Medical Information Bureau (MIB). This report includes MIB codes which provide detail on prior insurance applications submitted to other member companies by the person in question.

MVR—The Motor Vehicle Record (MVR) provides a history of driving criticisms, if any, for a given applicant. This inexpensive and readily available data source provides important information on the applicant's risk profile otherwise unavailable in third-party marketing data. Due to its protective value, it is also a common underwriting requirement for many life insurers.

Electronic Rx Profile—in recent years, several firms have started collecting prescription data records from pharmacy benefit managers nationwide, compiling by individual, and selling this information to insurers. Many users are enthusiastic about its protective value, and as a result it is becoming a standard underwriting requirement for an increasing number of life insurance companies. This is another interesting source for predictive modeling.

Other traditional underwriting requirements, such as blood and urine analysis, EKG's, medical records and exam, etc., would add predictive power to a model, but the time and cost to include them may negate the benefits.

Non-traditional third-party data sets come in a variety of shapes and forms, but most recently we have seen the application of marketing and consumer credit data from companies such as Equifax and Axiom. It is important to distinguish between marketing data and the credit score information for which these consumer reporting agencies are better known. Beyond the credit data, these firms also collect and distribute consumer information for marketing purposes. Whenever you use your credit card to make a purchase, or provide your phone number or zip code to the cashier, this data is being collected, aggregated, and resold.

The third party marketing dataset obtained from the consumer credit company contains thousands of fields of data. In contrast to the credit score data, is not subject to the Fair Credit Reporting Act (FCRA) requirements, and does not require signature authority by the insurance applicant to use it in a model. For the purposes of constructing a model, the data can be returned without personally identifiable information. Our experience indicates that using an individual's name and address, the typical match rate for members of these databases is over 95 percent.

We understand if some people react to this with a feeling of someone looking over your shoulder, and we discuss some of the ethical concerns of using this data in a later section of this article. Here we will simply say that while many of these data fields are quite interesting for life underwriting, it is important to note that model scores are not highly dependent upon any one, or even handful of them. Instead, the picture painted by this data is viewed holistically, trends are identified that are not necessarily noticeable to the naked eye, and the overall messages about lifestyle and mortality risk are communicated. For this reason, it is difficult, if not impossible, to send a powerful message that misrepresents the applicant, or for the applicant to manipulate the data in a misleading fashion.

Modeling Process

The first step in the model building process is to collect and organize all this data. For several reasons, it is collected for applications received by the insurer over the past 12 to 18 months. Depending upon the volume of applications received, this time frame typically produces a sample of underwriting decisions which will be large enough to sufficiently remove the statistical variation in the model, and ensure the third-party data available is still relevant. To clarify, the external data technically reflects the applicant's lifestyle today, but is still an accurate representation of them when they applied for insurance provided that time was in the recent past. Based on our experience, 18 months is about when you may begin to see material changes in the modeling data, and thus question its applicability to the application date.

The actual collection of the third-party marketing data set for model building is typically a painless process facilitated by the provider, but the availability of internal historical underwriting data can vary greatly depending upon individual company practices.

Once the data is collected into one centralized data set and loaded into the statistical package in which the analysis will be performed, data preparation will provide a solid foundation for model development. Data preparation can be summarized into four steps which are described below:

1. Variable Generation
2. Exploratory Data Analysis
3. Variable Transformation
4. Partitioning Model Set for Model Build

Variable Generation

Variable generation is the process of creating variables from the raw data. Every field of data loaded into the system, including the target and predictive variables, is assigned a name and a data format. At times this is a trivial process of mapping one input data field to one variable with a descriptive variable name. However, this step can require more thought to build the most effective predictive models. Individual data fields can be combined in ways that communicate more information than the fields do on their own.

These synthetic variables, as they are called, vary greatly in complexity. Simple examples include combining height and weight to calculate BMI, or home and work address to calculate distance. However, in our experience some of the most informative predictive variables for life insurance underwriting are what we call disease-state models. These are essentially embedded predictive models which quantify the likelihood an individual is afflicted with a particular disease such as diabetes, cardiovascular, or cancer. The results of these models can then be used as independent predictive variables in the overall underwriting model. Synthetic variables are where the science and art of predictive modeling come together. There are well-defined processes which measure the correlations of predictive variables with a target, but knowing which variables to start from relies more on experience and intuition.

Exploratory Data Analysis

Before even considering the relationship between independent and dependent variables, it is first important to become comfortable with the contents of the modeling data by analyzing the distributional properties of each variable. Descriptive statistics such as min, max, mean, median, mode, and frequency provide useful insight. This process tells modelers what they have to work with, and informs them of any data issues they must address before proceeding.

After the initial distributional analysis, the univariate (one variable at a time) review is extended to examine relationship with the target variable. One-by-one, the correlation between predictive and target variable is calculated to preview of each variable's predictive power. The variables that stand out in this process will be highly correlated with the target, well populated, sufficiently distributed, and thus are strong candidates to include in the final model.

In addition to paring down the list of potential predictive variables, the univariate analysis serves as a common sense check on the modeling process. Underwriters, actuaries, and modelers can sit down and discuss the list of variables which show strong relationships. In our experience, most of the variables that appear are those which underwriters will confirm are important in their processes. However, some other variables that are present can be a surprise. In these cases, further investigation into the possible explanations for the correlation is advisable.

Variable Transformation

The exploratory data analysis will most likely reveal some imperfections in the data which must be addressed before constructing the model. Data issues can be mitigated by several variable transformations:

1. Group excessive categorical values
2. Replace missing values
3. Cap extreme values or outliers
4. Capture trends

To increase the credibility of relationships in the data, it is often helpful to group the values of a given predictive variable into buckets. For example, few people in the modeling data are likely to have a salary of exactly $100,000, which means it is difficult to assign statistical significance to the likelihood an individual with that salary to be underwritten into a particular class. However, if people with salaries between $90,000 and $110,000 are viewed as a group, it becomes easier to make credible statements about the pattern of underwriting classes for those people together.

Missing values for different variables among the records in a data set is sometimes problematic. Unfortunately, there is no simple solution to retrieve the true distribution of variables that have missing values, but there are several approaches that help mitigate the problem. Modelers could remove all records in the data set which have missing values for certain variables, but this may be not an ideal solution because it can create a biased sample or remove useful information. A more common and effective solution is to replace the missing values with a neutral estimate or a best estimate. The neutral estimate could be a relatively straightforward metric such as the mean or median value for that variable, or a more in depth analysis of the best estimate could be the average value for that variable among other records that most similar to the one in question.

Almost all data sets a modeler encounters in real life will contain errors. A common manifestation of these errors is extreme values or outliers which distort the distribution of a variable. While not every outlier is a data error, modelers must weigh the risks and benefits of skewing the overall distribution to accommodate a very small number of what may or may not be realistic data points. Smoothing these extreme values may be a poor idea in applications such as risk management where the tail of the distribution is of utmost concern, but for underwriting predictive modeling it is often worthwhile to focus more on the center of the distribution. One approach to reducing the distortion is to transform a variable to a logarithmic scale. While extreme values will be muted, log transformation may minimize the original trend. Capping extreme values at the highest "reasonable" value is another simple alternative.

Finally, transforming variables from text categories to numerical scales can capture trends more readily. For example, BMI ranges have been officially classified into four categories: under-weight, normal, over- weight, and obese. Applicants with normal range of BMI are associated with a lower health risk than the members of the other categories. The trend of the BMI can be captured more effectively by transforming the BMI categories into an ordinal rank with higher numbers representing higher health risks, for example, 1=normal, 2=over-weight, 3=under-weight, and 4=obese.

Partitioning Model Set for Model Build

After collecting the data, preparing each variable, and casting aside those variables which will not be helpful in the model, the data set is divided into three approximately equal parts. Two of these, commonly called the "train" and "validation" sets, are for model building, while the "test" is placed aside until the end of the process where it will be used to assess the results [20].

After the data sets are partitioned, modelers carry out an iterative process that produces the strongest model. Most model builds will test a variety of statistical techniques, but often one effective, and therefore very common approach, is stepwise regression [21]. This is a fairly complicated process, but in essence, a best fit line that maps a set of predictive variables to the target is created. In a linear model, this best fit line will be of the form A * variable1 + B * variable2 + . . . = target variable. Variables are added and removed one-by-one, each time calculating the new best fit line, and comparing the fit of the new line with the fits of those created previously. This process reveals the marginal predictive power of each variable, and produces an equation with the most predictive power that relies upon the smallest number of predictive variables.

Each variable that survives the univariate review should be correlated with the target, but because it may also be correlated with other predictive variables, not every variable that appears strong on its own will add marginal value to the model. Among a group of highly correlated variables, stepwise regression will typically only keep the one or two with the strongest relationships to the target. Another approach for dealing with highly correlated variables is to conduct a principal components analysis. Similar to the disease-state models described above, a principal component is a type of sub-predictive model that identifies the combination of correlated variables which exhibits the strongest relationship with the target. For example, a principal components analysis of a group of financial variables may reveal that A * income + B * net worth + C * mortgage principal, and so forth, is a better predictor of underwriting decision than these variables are on their own. Then result of this equation will then be the input variable used in the stepwise regression.

The model is first built using the training data, but modelers are also concerned about fitting the model too closely to the idiosyncratic features of one sample of data. The initial model is adjusted using the validation data in order to make it more general. Each set is only used once in the modeling process. It cannot be recycled since the information has already become part of the model; and reusing it would result in over-fitting.

To assure the model does not reflect patterns in the modeling data which are not repeated in the hold- out sample, and most importantly, are less likely to be repeated in the applications the company will receive in the future, the test set is used only to assess the results when modeling is completed. This step protects predictive modeling from pitfalls like back-testing investment strategies. It is almost always possible to find a pattern in data looking backwards, but the key question is whether that pattern will continue in the future. Due to the relative efficiency of financial markets, investment strategies which looked so promising in the past usually evaporate in the future. However, in predictive modeling we generally find that the models built on the train and validation data set hold up quite well for the test data. The results shown in Figures 1 and 2 are representative of model fit on past test data sets.

At the end of this process modelers will have identified the equation of predictive variables that has the strongest statistical relationship with the target variable. A high score from this model implies the applicant is a good risk, and low score means the opposite. However, this is not the last step in model development. Layering key guidelines from the existing underwriting process on top of the algorithm is also a powerful tool. For example, certain serious but rare medical impairments may not occur in the data with the sufficient frequency to be included in a statistical model, but should not be overlooked by one either. For these conditions, it can be helpful to program specific rules that a life insurer uses to govern their underwriting. In addition to acting as a fail safe for rare medical conditions, the underwriting guidelines can also serve as the basis for making underwriting decisions. In the applications we have discussed thus far, the model has the authority to determine whether further underwriting is needed, but not to lower an insurance offer from the best underwriting class. Even for applicants where the model would recommend a lower underwriting class, incorporating the underwriting guidelines provides an easily justifiable reason for offering that class.

A final tool to extract useful information out of the modeling data is a decision tree [22]. A decision tree is a structure that divides a large heterogeneous data set into a series of small homogenous subsets by applying rules. Each group father along the branches of the tree will be more homogeneous than the one immediately preceding it. The purpose of the decision tree analysis is to determine a set of if-then logical conditions that improve underwriting classification. As a simple example, the process starts with all applicants, and then splits them based upon whether their BMIs are greater or lower than 30.

Presumably, applicant with BMI's lower than 30 would have been underwritten into a better class than those with higher BMIs. The stronger variables in the regression equation are good candidates for decision tree rules, but any of the data elements generated thus far, including predictive variables, the algorithm score itself, and programmed underwriting rules, can be used to segment the population in this manner. Figure 3 displays this logic graphically.

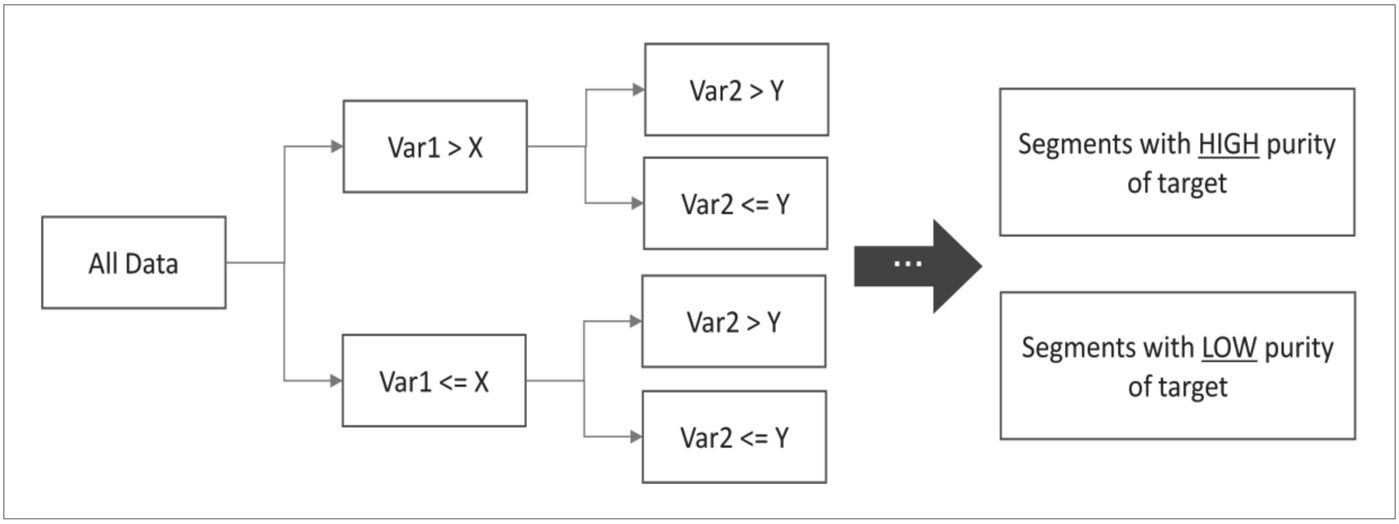
In principal, decision trees could be constructed manually, but in practice, dedicated software packages are much more efficient in identifying the data elements and values upon which to segment the population. These packages essentially take the brute force approach of trial and error, but due to computational efficiency they are able to develop optimal multi-node decision trees in manageable time.

Monitoring Results

In a previous section we discussed how to use the information revealed by predictive models to generate significant operational efficiencies in the underwriting process. From a technical standpoint, implementing a predictive modeling application can occur in many different ways. Given the depth of the topic, this paper leaves these aspects of implementation for a future discussion. However, we would like to address one area which we believe should be strongly considered a focus after implementation.

As with traditional underwriting practices, it is critical to monitor the results of a process change. Since a predictive model is built from a static sample of policyholders who were actually underwritten using the traditional process, it is important to consider how using it to assess the health risk of a dynamic population of new applicants may result in anti-selection. Is there potential for applicants and producers to game the system and

Figure 3
Graphical Representation of Decision Tree



exploit the reduced requirements? There are several avenues through which life insurers can guard against anti-selection.

First, the third party marketing data cannot be easily manipulated by the applicant. It is reported directly by the third-party agency, and is based upon trends captured over time rather than sudden changes in behavior. Moreover, the model does not rely on any one field from this data, but rather uses it to form a general understanding about a person's lifestyle. It would be very difficult for an applicant to systematically alter behavior over time so it presents a false impression. In fact, if the applicant were successful in systematically altering behavior to change his or her profile, more than likely the applicant's mortality risk would have also changed in the same direction.

To supplement the protection offered by the third party data, it is advisable to maintain a certain degree of unpredictability in which applicants will be allowed to forgo additional requirements. The combination of risk factors that qualify an applicant for reduced requirements at each underwriting class is typically sufficiently complex to offer an initial defense against producers seeking to game the system. While the patterns are not simple enough to be picked up upon easily, we also recommend a percentage of applicants who do qualify be selected at random for traditional underwriting. This will both further disguise the profile of applicants who are eligible for streamlined underwriting, and offer a baseline for monitoring results. If evidence of anti-selection is present in these applicants, the insurer will be alerted of the need to alter the process. As in traditional underwriting, producers will seek to exploit differences in criteria to obtain the best offer for their clients, but this application of predictive modeling does offer important safeguards against potentially damaging behavior.

LEGAL AND ETHICAL CONCERNS

Predictive modeling in life insurance may raise ethical and legal questions. Given the regulations and norms that govern the industry, these questions are understandable. The authors of this paper are not legal experts, but we can offer our insight into several issues, and say that in our experience, it is feasible to assuage these concerns.

Collecting any data about individuals is a sensitive subject. Data collection agencies have been around since the late 19th century, but in the 1960s lawmakers became concerned with the availability of this data as they worried that the rapidly developing computing industry would vastly expand its influence, and lead to potential abuses. This concern resulted in the Fair Credit Reporting Act (FCRA) of 1970. The essence of the law is that provided certain consumer protections are maintained around access and transparency, the efficiency gains of making this data available are worthwhile. We tell this story as a kind of aside because it is the first question asked by many with whom we have discussed predictive modeling. However, as described above, the data provided by the aggregators come from their marketing sets which are not subject to the FCRA.

Even though the third-party marketing data does not face explicit FCRA or signature authority legal restrictions, it can still raise ethical question about whether utilizing the consumer data is overly invasive. The first point to realize is that commercial use of this personal data is not new. For many years it has been a valuable tool in selling consumer goods. Marketing firms build personal profiles on individuals which determine what type of catalogs and mailing advertisements they receive. Google scans the text of searches and emails in order to present people with related advertisements. We believe society has accepted this openness, not without hesitation, because on average it provides more of what we want, less of what we do not. In addition to consumer marketing applications, predictive modeling using third-party consumer data has also been accepted for property and casualty insurance underwriting.

Despite its acceptance in other fields, life insurance has a unique culture, set of norms, and regulations, so additional care must be taken to use this data in ways that are acceptable. A critical step in predictive model development is determining which variables to include in the model. We have described the statistical basis on which these decisions are made, but the process also considers regulatory and business concerns. Before beginning the model build, the legal and compliance functions of the life insurer should be the first to review the list of potential variables. No matter what their predictive powers may be, any variable that is deemed to create a legal or public relations risk, or is counter to the company's "values" should be excluded from the model. Even if not explicitly forbidden by regulations, life insurers should err on the side of caution and exclude variables which convey questionable information, and can feel confident that this caution will not cripple the strength of the model.

The legal and ethical concerns raised also depend upon business decisions that the model is allowed to influence. While in principal, predictive models could play the lead role in assigning underwriting classes for many applicants, insurers have been most comfortable from a compliance perspective utilizing models to triage applications. By using the model as described above to inform the insurer when no further requirements are needed, the model does not take adverse actions for any applicant. In fact, the model only has the potential to take a positive action by offering a streamlined underwriting process that would otherwise be unavailable.

We fully expect and understand that questions will be raised when changes occur to a consumer-facing process like underwriting. We also recognize that predictive modeling is a new and growing trend in life insurance, and the industry culture and regulations may evolve to in ways that impact how data and models are used. For both of these reasons, company legal and compliance experts are key members of every predictive modeling project we agree to support. While we do not claim to be the definitive source on this subject, in our experience thus far, it has been possible to utilize predictive modeling for life insurance underwriting in ways that are compatible with regulatory, ethical, and cultural concerns.

THE FUTURE OF LIFE INSURANCE PREDICTIVE MODELING

Due to rapid improvements in computation power, data storage capacity, and statistical modeling techniques, over the last several decades predictive modeling has come into widespread use by corporations looking to gain a competitive advantage. Banking and credit card industries are well known pioneers for modeling credit card fraud, personal financial credit score for mortgage and loan application, credit card mail solicitation, customer cross-sale, and more.

While insurance has lagged behind other industries, more recently it has gained momentum in data mining and predictive modeling. Early developments include the use of personal financial credit history for pricing and underwriting for personal automobile and homeowners insurance. As it proved successful in personal lines, predictive modeling has spread into commercial insurance pricing and underwriting, as well as into a variety of other applications including price optimization models, life-time customer models, claim models, agency recruiting models, and customer retention models. In just the last several years, predictive modeling is beginning to show promise in the life insurance industry.

Until relatively recently, merely using predictive models to support underwriting, pricing and marketing gave property and casualty insurance companies a competitive edge. However, data analytics has sufficiently penetrated the market so first mover advantages no longer exist. Property and casualty companies must now improve their modeling techniques and broaden the applications to stay ahead of their competition [23]. Because application of data mining and predictive modeling is, for the most part, still new and unexplored territory in life insurance, we do believe those who act first will realize similar first mover gains.

Our experience indicates that using predictive modeling for underwriting can empower life companies to segment and underwrite risks through a more consistent and less expensive process. In doing so, they can reduce costs, improve customer and producer experience, and generate substantial business growth. Tomorrow, we anticipate those who ignore this emerging trend will scramble to catch up while the initial users have moved to models of mortality. As a first step in modeling mortality directly, we have experimented with modeling the main cause of death in the short-term, accidents. At younger ages, insured mortality is driven by accidental death rather than by disease.[1] A sample model we have built to segment which members of a population have been involved in severe auto accidents has shown substantial promise, and is being incorporated into the latest projects we have supported. The more we discuss full-scale models of mortality with insurers, the more excited they become about their potential, and committed to unearthing the data to make them a reality. We believe that day is near.

We would like to close by noting that improvements to efficiency and risk selection will not only accrue to insurers, but also to individuals. Over time, competition will drive insurers to not only capture additional profits from their reduced costs, but also charge lower premiums and require fewer medical tests. Because the predictive models we describe do not disadvantage individual applicants, we believe the long run effect of predictive modeling will be to increase access to insurance. And if the final effect of predictive modeling in life underwriting is in some small way to push people toward healthier lifestyles, we would be happy to claim that as the ultimate victory. ■

Chris Stehno is managing director at Deloitte Consulting LLP. He can be reached at *cstehno@deloitte.com*.

Jim Guszcza is the US chief data scientist of Deloitte Consulting, and a member of Deloitte's Advanced Analytics and Modeling practice. He can be reached at *jguszcza@deloitte.com*.

ENDNOTES

1 According to the National Center for Health Statistics National Vital Statistics Reports from March 2005, the top three causes of death among young adults aged 25-29 are each acute injuries. These account for 61.58 percent of all deaths at those ages. The leading cause of death is accidental injury (34.09 percent), followed by homicide (14 percent), and suicide (13.49 percent).

REFERENCES

1 Davenport, T. H., Harris, J. G., *Competing on Analytics: The New Science of Winning*, Harvard Business School Press, (2006).

2 Guszcza, J., "Analyzing Analytics"*, Contingencies,* American Academy of Actuaries, July- August, (2008).

3 McCullagh, P., Nelder, J. A., *Generalized Liner Models*, 2nd Edition, Chapman and Hall, (1989).

4 Brockman, M. J., Wright, T. S., "Statistical Motor Rating: Making Effective Use of Your Data," *Journal of the Institute of Actuaries*, Vol. 119, Part III, (1992).

5 Mildenhall, S.J., "A Systematic Relationship between Minimum Bias and Generalized Linear Models," *Proceedings of Casualty Actuarial Society*, Vol. LXXXVI, Casualty Actuarial Society, (1999).

6 Bailey, R. A., Simon, L. J., "An Actuarial Note on the Credibility of a Single Private Passenger Car", *Proceedings of Casualty Actuarial Society*, Vol. LVII, Casualty Actuarial Society, (1959).

7 Bulhmann, H., "Experience Rating and Credibility", *ASTIN Bulletin IV*, Part III, (1967).

8 "Insurance Scoring in Private Passenger Automobile Insurance – Breaking the Silence," *Conning Report,* Conning, (2001).

9 *Report on the Use of Credit History for Personal Line of Insurance*, American Academy of Actuaries, (2002).

10 "The Top 10 Casualty Actuarial Stories of 2009," *Actuarial Review*, Vol. 37, No. 1, Casualty Actuarial Society, (2010).

11 Guszcza, J., Wu, C. P., "Mining the Most of Credit and Non-Credit Data", *Contingencies,* American Academy of Actuaries, March-April, (2003).

12 Meehl, P., *Clinical Versus Statistical Prediction: A Theoretical Analysis and a Review of the Evidence*, University of Minnesota Press, (1954).

13 Gladwell, M., *Blink: The Power of Thinking without Thinking*, Little Brown and Co, (2005).

14 Lewis, M., *Moneyball: the Art of Winning an Unfair Game,* W. W. Norton & Company, (2003).

15 Ayres, I., *Super Crunchers: Why Thinking-by-Numbers Is the New Way to Be Smart,* Bantam Books, (2007).

16 Gladwell, M., "The Formula", *The New Yorker*, (2006).

17 Meehl P., "Causes and Effects of My Disturbing Little Book," *Journal of Personality Assessment*, Vol. 50, (1986).

18 Dawes, R., Faust, D., Meehl, P., "Clinical Versus Actuarial Judgment," *Science,* 243: 1668-1674, (1989).

19 Guszcza, J., Batty, M., Kroll, A., Stehno, C., "Bring Predictive Models to Life," *Actuarial Software Now - A Supplement to Contingencies*, American Academy of Actuaries, Winter, (2009).

20 Hastie, T., Tibshirani, R., Friedman, J. H., *The Elements of Statistical Learning*, Springer, (2003).

21 Berry, M. J. A., Linoff, G. S., *Data Mining Techniques: For Marketing, Sales, and Customer Relationship Management*, John Wiley & Sons, (2003).

22 Breiman, L., Friedman, J., Olshen, R., Stone, C., *Classification and Regression Trees*, New York: Chapman and Hall, (1993).

23 Yan, J., Masud, M., Wu, C. P., "Staying Ahead of the Analytical Competitive Curve: Integrating the Broad Range Applications of Predictive Modeling in a Competitive Market Environment," *CAS E-Forum*, Winter, Casualty Actuarial Society, (2008).

24 Stehno, C., Johns, C., "You Are What You Eat: Using Consumer Data to Predict Health Risk," *Contingencies*, American Academy of Actuaries, Winter, (2006).

25 Yi Zhang , Jonathan Koren, Efficient bayesian hierarchical user modeling for recommendation system, Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval, July 2007, Amsterdam, The Netherlands.

2018 ANNUAL MEETING
& EXHIBIT
NASHVILLE, TENNESSEE
OCT. 14–17, 2018
SAVE THE DATE
Staying in tune
WITH THE PROFESSION
SOCIETY OF ACTUARIES®

SOCIETY OF ACTUARIES®

475 N. Martingale Road, Suite 600
Schaumburg, Illinois 60173
p: 847.706.3500 f: 847.706.3599
w: www.soa.org

NONPROFIT
ORGANIZATION
U.S. POSTAGE
PAID
SAINT JOSEPH, MI
PERMIT NO. 263