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Product Matters!

Indexed Variable Annuities: The Next Product Frontier for the U.S. Annuity Market

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Chairperson's Corner

By Brock Robbins

Welcome to the first issue of *Product Matters!* for 2018 and my first dispatch from the Chairperson's Corner. I've been serving as a volunteer on the Product Development Section Council for three years now. I'm honored and delighted to step into the role of council chair.

I feel fortunate to work in the actuarial field where vocational pride is strong, and so many SOA members are willing and able to give back to the profession. This newsletter along with other activities of the PD Section Council reflect the commitment that many of you have made to keeping our professional body strong and helping to shape its future.

In this edition of *Product Matters!*, four industry experts address a range of topical issues affecting life and annuity products.

- Simpa Baiye, Robert Humphreys and David Knipe offer a closer look at indexed variable annuities, a product that continues to perform well as retirees and pre-retirees seek more attractive accumulation opportunities than those offered by fixed annuities and fixed indexed annuities.
- Paul Hance and Heather Gordon provide an update on changes coming to statutory valuation rates that will affect single premium immediate annuity products. The impact, they stress, can be significant.
- Marc Vincelli discusses smoking trends by geography and demographics and the impact of a changing smoking rate on population-level mortality improvement.
- Rounding out this issue is part one of a two-part article on predictive modelling in life insurance, by a team of authors sponsored by Deloitte and highlights from the 2017 Annual Meeting & Exhibit from presenters and attendees.

I want to thank each of our contributing authors for volunteering their time and valuable expertise. Your efforts are greatly appreciated!

I highly recommend getting involved with the section council—volunteer opportunities abound! You can serve on a committee, take a short-term volunteer opportunity and *Product Matters!* editors are always on the hunt for contributors with a new perspective on relevant product development topics. The SOA Volunteers Opportunities database (located on the SOA website) is a great place to check for opportunities to get more involved.

The Product Development Section is one of the largest and most active groups within the SOA. The section has multiple activities underway at any given time. If you're interested in finding out how to get involved, I encourage you to contact me or one of the other council members listed on the inside front cover of this newsletter. There's no better way to expand your professional network, sharpen your communication skills and stay abreast of the myriad influences that keep life insurance and annuity business in a constant state of change.

I'm excited about the work we have planned for the upcoming year. I hope you will join me and members of the Product Development Section Council in making this a most productive year. ■

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Indexed Variable Annuities: The Next Product Frontier for the U.S. Annuity Market

By Simpa Baiye, Robert Humphreys and David Knipe

Indexed variable annuities (IVAs)—also known as "structured" or "buffer" annuities—are a relatively new product that have drawn interest both among insurers and investors. IVAs have traits insurance companies and customers find attractive, but complex financial reporting and compliance considerations accompany them. In order for actual and potential issuers and other interested parties to better understand the nature of these products, we discuss in this article:

- product design,
- product engineering,
- issuance,
- asset-liability management, and
- accounting considerations across regulatory and GAAP accounting frameworks.

WHAT ARE INDEXED VARIABLE ANNUITIES?

Indexed variable annuities (IVAs) (also known as "structured" or "buffer" annuities) are a relatively new deferred annuity product. An IVA is essentially a deferred annuity that provides equity index-linked accumulation potential with some exposure to downside market performance. IVAs stand in contrast to fixed indexed annuities (FIAs), which provide limited exposure to positive index returns and no exposure to downside performance, and also to variable annuities, which provide full exposure to market performance. Figure 1 demonstrates this design feature by illustrating periodic rates of return (or credited rates) for one IVA design relative to other types of annuities and for various levels of equity market returns.

IVA sales have grown steadily since their introduction to the U.S. annuity market in 2012. Industry sales figures in Figure 2 point to growing market acceptance of these annuities. Anecdotal surveys indicate that sales growth has been driven by retirees and pre-retirees seeking more attractive accumulation opportunities relative to those offered by fixed annuities and fixed indexed annuities. We thus expect IVAs to feature more in insurers' product lineups in the near future.

IVA DESIGN

IVAs consist of crediting accounts for renewable terms wherein periodic interest credits (positive or negative) are linked to the performance of a reference equity index via a formula. The crediting formula places limits on upside performance that accrues and also provides defined limits on how negative performance is passed on to the contracts. Figure 3 illustrates (assuming that the length of the crediting strategy term is one year) the crediting rate potential for three different crediting designs that are prevalent as of 2017. IVA 1 provides crediting rates that vary directly with the market and up to a predefined limit, along with negative credits that apply to the extent that the market drops below a defined level. IVA 2 provides crediting rates that vary directly with market returns up to a predefined limit with negative credits that both apply as markets drop and level off at a defined loss level. IVA 3 provides a fixed credited rate as long as market returns are zero or greater, along with negative credits that apply to the extent that the market drops below a defined level.

Early redemptions typically involve some upward or downward adjustment to the initial deposit for the interim value of index credits and also potentially for the market value of the bonds backing product reserves.

Traditional variable annuity subaccounts and fixed-rate accounts are often offered alongside IVA crediting options. In some instances, IVAs feature limited insurance guarantees such as guaranteed death benefits or waivers of otherwise applicable contingent deferred sales charges.

PRODUCT ENGINEERING

The financial building blocks for IVAs comprise a bond component and derivatives component made up of complementary positions in equity index options. For IVA strategy 1 illustrated in Figure 3, the IVA effectively consists of a zero-coupon bond, a European call option that is bought, and a European put option that is simultaneously sold. The call option provides the upside index potential, while the put option puts the bond investment at risk should index performance be negative. The performance of this structure is illustrated in Figure 4 under a variety of annual index return scenarios.

Figure 1
Annuity Returns Comparison

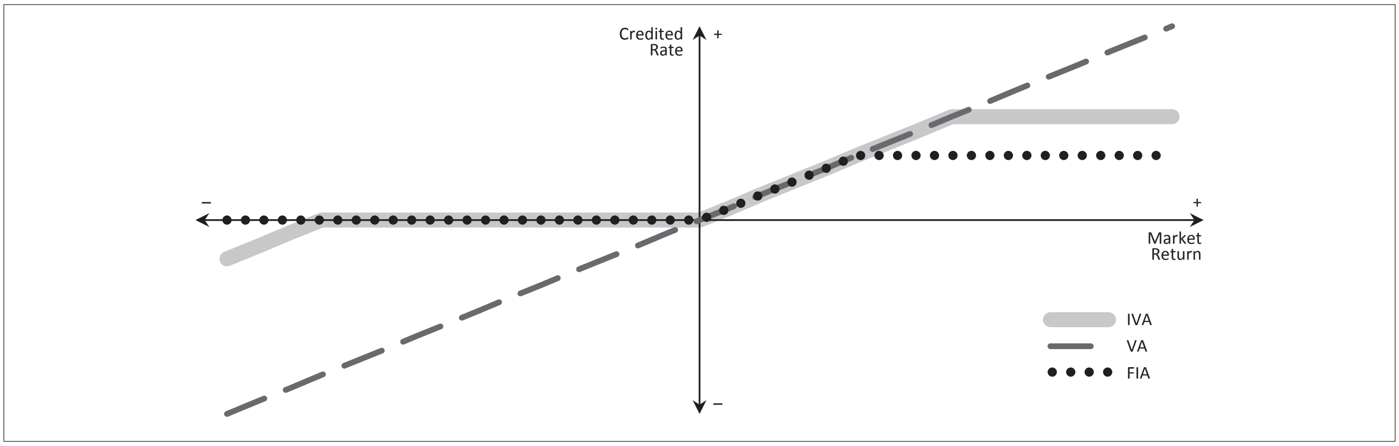
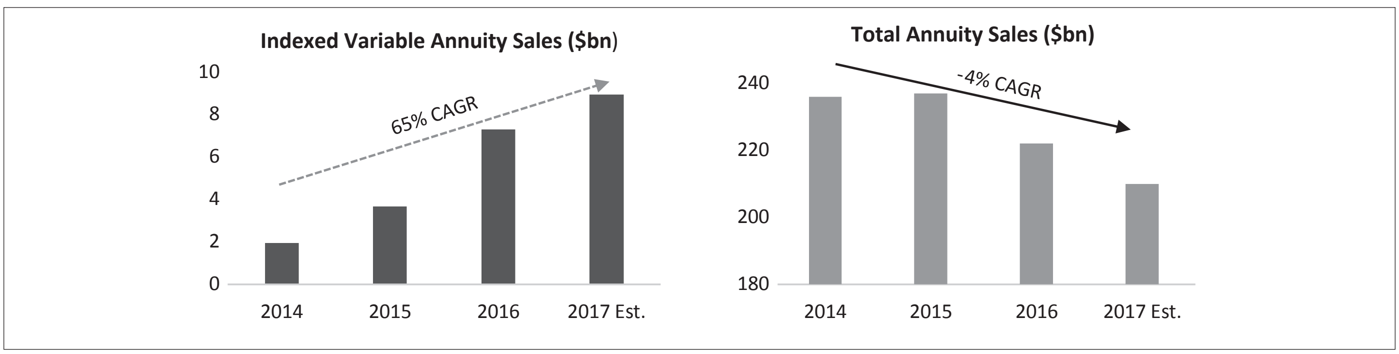


Figure 2
Annuity Sales by Year



Source: LIMRA Secure Retirement Institute

Figure 3
IVA Crediting Strategies

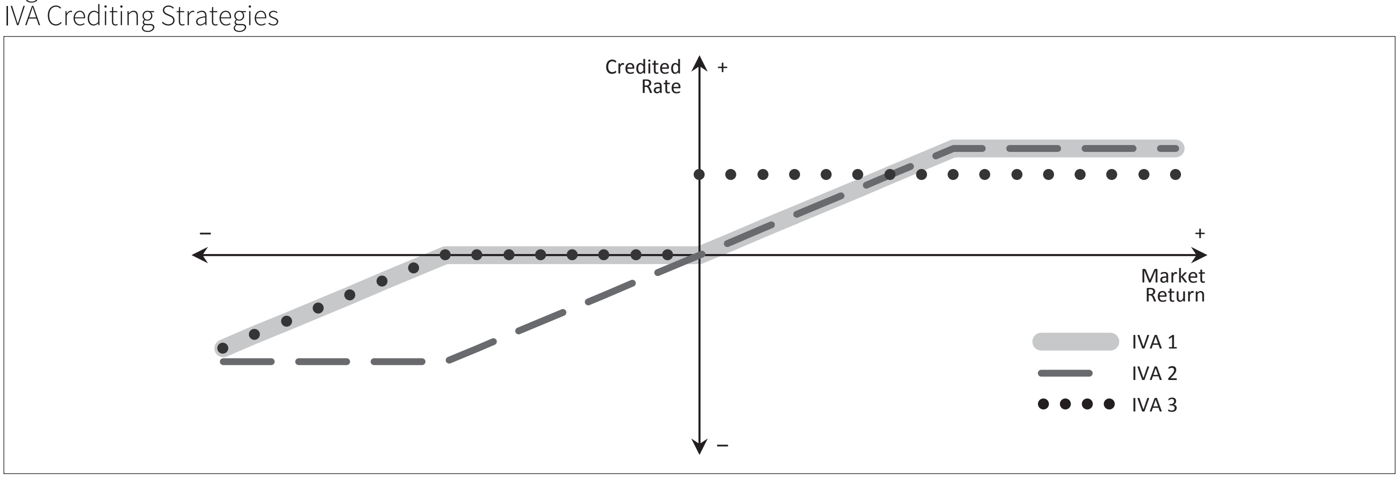
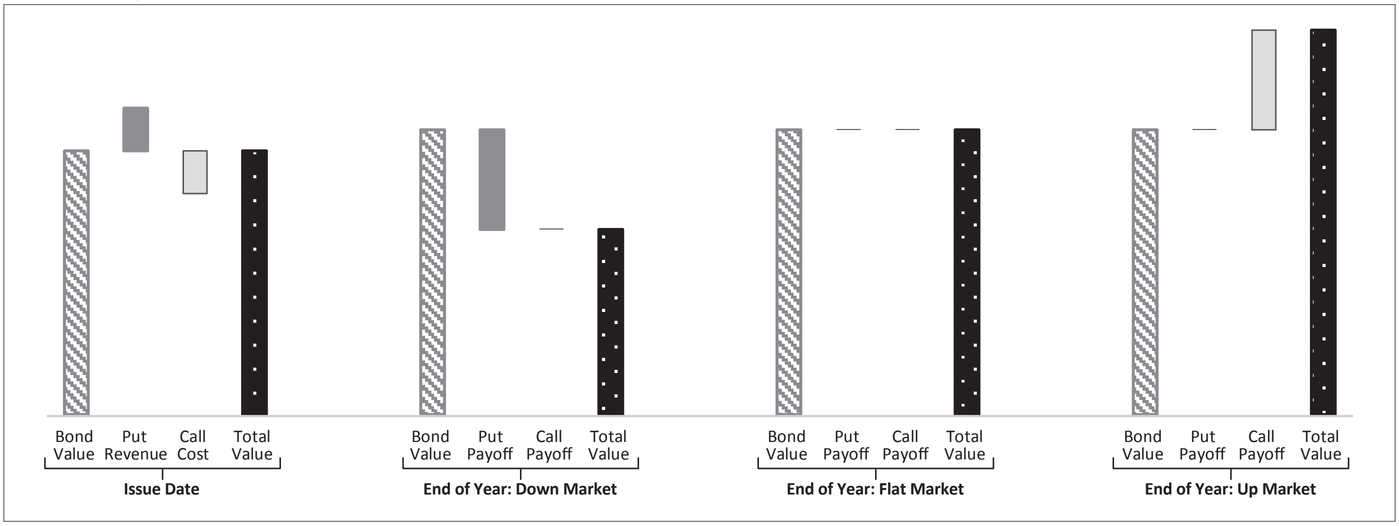


Figure 4
IVA Building Blocks



The decomposition in Figure 4 helps clarify how insurers could manage IVA risks. It also provides a clear path towards interim redemption value calculations for policyholders.

Insurer profit margins come from explicit product fees, spreads on investments made with premium deposits, and differentials (if any) between the revenue generated from the sale of derivatives (that provide downside exposure) in excess of purchase prices of options that provide upside market potential.

ASSET-LIABILITY MANAGEMENT

Bond Component

Insurers can hedge the bond component by investing contract deposits in fixed income securities. Fixed-income investments generate yield that accrues to the insurer and for which the insurer may take some credit, interest-rate, and liquidity risk. The duration, liquidity and credit risk of the bond investment should reflect product design, the likelihood of withdrawals and redemptions, and the ongoing need for collateral to back any derivatives traded to fund index-linked crediting.

Derivatives Component

Interest crediting can be hedged by simultaneously purchasing call options with the proceeds of a simultaneous sale of put options. The anticipated yield on fixed-income investments may also contribute towards the purchase of call options. Call options can be purchased on an exchange-traded or over-the-counter (OTC) basis.

Put options can be sold on both an exchange-traded or OTC basis to derivatives dealers. Put options could in theory also be traded internally to meet the demand for put options to support the hedging of existing variable annuity guarantee business.

Regulatory requirements can have a meaningful impact on the extent to which economic asset-liability management can be practiced. Regulation 128 in New York, as an example, effectively places constraints on investments made with IVA product deposits. Such regulatory limits on asset-liability risk tolerances could indirectly influence product design options and asset-liability management alternatives.

PRODUCT ISSUANCE

The statutory product form for an IVA would in most cases be a modified guaranteed annuity (MGA) or a variable annuity. MGAs are effectively deferred variable annuities which guarantee a rate of return only if held for a defined period. Modified guaranteed annuities are subject to regulations which impact (among other things) product features, the creation of guaranteed separate accounts for IVAs, and the market valuation of assets backing reserves.

Inherent in the product design for IVAs is the possibility that policyholders may lose part or all of their initial deposits at contract maturity. For this reason, IVAs require registration under the 1933 securities act. Issuance under securities laws is complemented by the establishment of non-unitized, guaranteed separate accounts which house assets backing reserves. These separate accounts need to comply with relevant state laws.

Transfers between the separate account and the insurer's general account (as permitted) can be used to fund reserve requirements, ongoing derivative collateral requirements, provide insurer margins, and pay policy benefits.

US STATUTORY ACCOUNTING

The valuation of IVA insurance liabilities under SAP involves classifying the product within the appropriate valuation framework. IVA product design and ancillary features could be subject to valuation under Actuarial Guideline 43 (AG43) for insurance entities not effectively domiciled in New York. However, AG43 guidelines do not provide explicit prescriptions for the valuation of indexed variable annuities. As such, the specific path towards fulfilling valuation requirements would ideally consider both annuity minimum valuation standards and any conflicting interactions with economic asset-liability management. IVAs issued out of legal entities effectively domiciled in New York would have reserves computed in accordance with Regulations 151 and 128.

The valuation of investments backing IVAs in the separate account would be at market value, unless otherwise permitted by regulators. To the extent that reserves produced by the guideline do not share the same market sensitivity with assets backing the same, balance sheet volatility and redundancies may occur.

US GAAP ACCOUNTING

Valuation of IVA insurance liabilities under GAAP needs to take into account the embedded derivative inherent in the crediting design. As a result, ASC 815-15, which provides guidance on embedded derivatives, would apply and involve identifying the host contract and embedded derivative components of the product. The host contract would be accounted for as a debt instrument, typically at amortized cost, while the embedded derivative would be measured at fair value through income. An alternative method involves valuing the entire contract (both host contract and embedded derivative) using fair value principles by electing the Fair Value Option based on ASC 825, financial instruments.

Derivatives employed in hedging[1] the crediting option would be measured at fair value through the income statement. Fixed income investments backing the IVA contract would typically be classified as available for sale (AFS) or trading, or the fair value option could be elected. An AFS classification for fixed income securities involves recording unrealized gains or losses in other comprehensive income and would be least inconsistent with a host contract that is effectively measured at amortized cost, while a trading securities classification or the election of the fair value option for fixed income instruments and accounting for derivatives at fair value would be consistent with fair valuing of the entire annuity contract under ASC 825. A trading classification, or the election of the fair value option for the relevant fixed income securities would bring all realized and unrealized gains and losses into earnings.

IMPLICATIONS

Industry sales for indexed variable annuities should continue to grow as more insurers launch competing products in the growing IVA space. The design and risk-management approach for IVAs need to balance customer needs and insurer risk appetite.

Fixed income investments and margins from the trading of derivatives are key sources of profits for insurers. Accordingly, the optimal investment and derivatives-use strategy for an insurer will need to reflect product design and risk appetite, and requires detailed analysis.

A careful analysis of accounting and valuation approaches should occur with a clear view of the economic risk-management approach. This analysis will serve to minimize inconsistencies between GAAP and SAP accounting measures for both assets and IVA liabilities.

In conclusion, IVAs represent the next potentially sizeable opportunity for insurers to provide tax-deferred savings opportunities that meet the risk tolerances of a growing segment of pre-retirees. We anticipate continued product innovation in this space with the introduction of newer and more complex crediting designs. Product transparency will need to remain paramount as insurers manage legal and compliance risks that could come with the proliferation of these products.

For more information, please contact the authors of this article. ■

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ENDNOTE

1 The above does not refer to a formal designation of the hedge relationship in accordance with ASC 815, Derivatives and hedging.

SPIA Interest Rates in VM-22 for Stat Reserves

By Paul Hance and Heather Gordon

For the first time in over 30 years, changes are coming to the statutory valuation rates for Pension Risk Transfer and similar products! Over the last decade, it has become commonplace for single day transactions in the billion dollar plus range and the existing methodology, where an average of July to June yield rates is used, has started to make less sense. The lumpiness of these so-called "jumbo" transactions was one of the contributing factors leading regulators to ask the American Academy of Actuaries to help them with the development of a new interest rate methodology.

The result was the development, in less than two years, of a new interest rate methodology. This new methodology addresses issues raised by regulators, including how to handle lumpy jumbo transactions, modernization of the credit index, and better alignment of valuation rates with the assets backing the liabilities, while trying to build upon recently enacted regulatory requirements where it made sense.

The impact can be significant, especially for shorter duration liabilities. An American Academy of Actuaries analysis of a preliminary proposal similar to, but not exactly the same, as that adopted, showed up to a 2 percent decrease in the interest rate for short duration liabilities (A), around a 1 percent decrease for moderate duration liabilities (B & C), and similar interest rates for long duration liabilities (D).[1] See Figure 1.

The Statutory Valuation Rate changes are taking effect for contracts issued on or after Jan. 1, 2018. Products in scope for the new rates are:

- Single Premium Group Annuities (Pension Risk Transfer)
- Immediate Annuities
- Deferred Immediate Annuities (DIAs)
- Structured Settlements
- Payout Annuities (Settlement Options)
- Supplementary Contracts
- Living Benefits (GLWBs) and Contingent Deferred Annuities (CDAs) once account value is exhausted

The principles the American Academy of Actuaries working group used in the development of the methodology proposed to the NAIC were:

1. Valuation rates based on asset portfolios backing liability
2. Inclusion of appropriate prudence
3. Equal treatment across companies
4. Avoidance of perverse incentives
5. Consistency with other recent statutory frameworks
6. Daily valuation rate is ideal
7. Optimal tradeoff of accuracy and effort

A high level comparison of the current methodology and the resulting new methodology is shown in Table 1.

The current valuation rates use Moody's Long-Term Corporate Bond Index as the reference rate whose credit quality may not reflect the assets insurers are purchasing to back these liabilities. There is also only a single rate regardless of the duration of the liability. Taken together, these features of the current methodology could lead to carriers needing to post Asset Adequacy Testing (AAT) reserves.

The new methodology uses U.S. Treasuries plus VM-20 credit spreads and expected defaults. The distribution of credit quality is based on the public bond portion of an average life insurer's asset portfolio.

There will now be different rates for "Jumbo" contracts (initial premium greater than or equal to $250M) and "Non-Jumbo" contracts. Jumbo contracts will use a rate that is updated daily whereas Non-Jumbo contracts will use a rate that is updated quarterly.

Figure 1
SPIA Valuation Rates: Current vs. Proposed

Table 1
Current versus New Methodology

		Current	New
A	Reference Index	Moody's Long-Term Corporate Bond Index	Treasuries plus VM-20 Spreads
B	Credit Quality	Moody's Index	Based on Average Life Insurer Bond Portfolio
C	Prudence	20 percent of reference rate in excess of 3 percent	VM-20 Baseline Defaults and Spread Deduction
D	Floor	None, bias toward 3 percent	None
E	Valuation Rate Buckets	1	4 to reflect duration differences
F	Frequency of Updates	Annual	Quarterly (non-jumbo)/ Daily (jumbo)
G	Rounding	Nearest 25bp	Non-jumbo: nearest 25bp Jumbo: nearest 1bp

In addition, there will now be four different valuation rates to reflect differences in liability duration. For simplicity, there is a mapping based on two liability characteristics impactful to duration, age and the reference period (generally the certain period).

For contracts or certificates without life contingencies, Valuation Rate Buckets are assigned based on the length of the Reference Period* (RP), as follows:

RP ≤ 5Years	5Y < RP ≤ 10Y	10Y < RP ≤ 15Y	RP > 15Y
A	B	C	D

For contracts or certificates with life contingencies, Valuation Rate Buckets are assigned based on the length of the Reference Period (RP) and the Initial Age of the annuitant, as follows:

Initial Age	RP ≤ 5Years	5Y < RP ≤ 10Y	10Y < RP ≤ 15Y	RP > 15Y
90+	A	B	C	D
80–89	B	B	C	D
70–79	C	C	C	D
<70	D	D	D	D

*Reference Period - This is the rounded length of time until the last non-life-contingent payment.

The proposed rate changes were adopted by the Life Actuarial Task Force (LATF) of the National Association of Insurance Commissioners (NAIC) and are now incorporated into the Valuation Manual under VM-22. These rates replace the rates from the Standard Valuation Law under CARVM for these products.

Rates will be published by the NAIC at *http://www.naic.org/index_industry.htm*. The text of the regulation is at *http://www.naic.org/documents/cmte_a_latf_related_vm22_170407_adoption.docx*. For background on the development of the regulation, see *https://www.actuary.org/committees/dynamic/SVLMODERNIZATION*. ■

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ENDNOTES

1 Source: American Academy of Actuaries, SVL Interest Rate Modernization work group.

The Impact of a Changing Smoking Rate on Population-Level Mortality Improvement

By Marc Vincelli

The analysis of historical mortality improvement has traditionally focused on population-level experience segmented by age and gender, with little or no consideration given to smoker status as a potential confounder. It can be tempting to extend population-level results to one's own actuarial application without accounting for differences in smoking behavior between the study and target groups. However, as I discuss in this article, failing to understand and reflect differences in smoking behavior between groups can result in overstated (or understated) estimates of mortality improvement.

POPULATION SMOKING TRENDS

Smoking trends vary significantly by geography and a number of sociodemographic factors. These variations notwithstanding, there is little doubt that the overall proportion of Canadians and Americans who smoke has been in steady decline. According to data compiled by Statistics Canada, the prevalence of daily or occasional cigarette smoking in Canada for ages 12+ has declined from 23.0 percent in 2003 to 18.1 percent in 2014.[1] Similarly, data from the Centers for Disease Control and Prevention (CDC) in the U.S. indicates that the prevalence of daily or occasional cigarette smoking in the U.S. for ages 18+ has declined from approximately 20.9 percent in 2005 to 15.1 percent in 2015.[2] These aggregate trends translate into average annual cigarette smoking declines of approximately 2 percent to 3 percent per year on a relative basis.

The trends are even more stark when examined by age and gender. The tables in Figure 1 and Figure 2 illustrate cigarette smoking trends by gender and age group for each of Canada and the U.S., respectively. Note that cigarette smoking rates have declined more precipitously for adults under 45 than for adults 45+, after controlling for gender.

Figure 1
Proportion of Canadian Adults Who Smoke Cigarettes Daily or Occasionally (2003 vs 2014)[1]

Segment	2003 (%)	2014 (%)	Annualized Rate of Change (% Per Annum)
Males 20–34	33.5	29.6	–1.1
Males 35–44	31.2	25.9	–1.7
Males 45–64	24.5	22.9	–0.6
Males 65+	11.5	10.7	–0.7
Females 20–34	26.5	19.4	–2.8
Females 35–44	25.4	15.5	–4.4
Females 45–64	21.7	17.5	–1.9
Females 65+	10.5	8.4	–2.0

Figure 2
Proportion of U.S. Adults Who Smoke Cigarettes Daily or Occasionally (2005 vs 2015)[2]

Segment	2005 (%)	2015 (%)	Annualized Rate of Change (% Per Annum)
Males 18–24	28.0	15.0	–6.1
Males 25–44	26.8	19.8	–3.0
Males 45–64	25.2	17.9	–3.4
Males 65+	8.9	9.7	0.9
Females 18–24	20.7	11.0	–6.1
Females 25–44	21.4	15.8	–3.0
Females 45–64	18.8	16.1	–1.5
Females 65+	8.3	7.3	–1.3

IMPLICATIONS OF A CHANGING SMOKING RATE ON MORTALITY IMPROVEMENT

Having established that the overall cigarette smoking rate across Canada and the U.S. has been in decline over at least the past decade or so, I now discuss the implications of a changing smoking rate in the context of mortality improvement modeling.

The key implication of a changing smoking rate is that it alone can give rise to population-level mortality improvement (or deterioration). In other words, as the proportion of smokers in the group decreases, one can expect to observe mortality improvement by age and gender over time, simply by virtue of the flows between the higher mortality smoker and lower mortality non-smoker sub-groups. Conversely, as the proportion of smokers in the group increases, one can expect to observe mortality deterioration, all else being equal.

The key implication of a changing smoking rate is that it alone can give rise to population-level mortality improvement (or deterioration).

It is easy to overlook this type of smoking rate change-induced mortality improvement, and as we will see, it can be material. One danger of overlooking this component is that the practitioner models historical mortality improvement based on population-level data and subsequently extrapolates the results without adjustment to one or more groups with different smoking rates. In the event that population-level results are extrapolated without adjustment to smoker and non-smoker distinct groups—each of which by definition must have zero smoking rate change-induced mortality improvement—the practitioner risks using a materially overstated historical mortality improvement estimate *for each* of the smoker and non-smoker groups.

ESTIMATING THE MORTALITY IMPROVEMENT ARISING FROM A CHANGING SMOKING RATE

The component of population-level mortality improvement (MI) arising over one year from a changing smoking rate can be calculated using formula (1) below.

$$\text{One Year Population Level MI Arising from Change in Smoking Rate} = \frac{r}{\frac{1}{p(1-m)} - 1} \qquad (1)$$

where:

r = Relative change in smoking rate (% per annum)

p = Proportion of smokers at year start (i.e., smoking rate at year start)

m = Smoker mortality as a multiple of non-smoker mortality (i.e., smoker mortality / non-smoker mortality)

Note that formula (1) depends only on the assumed annual change in smoking rate (r), the proportion of smokers at year start (p), and the smoker/non-smoker mortality ratio (m); it is independent of the smoker and non-smoker mortality rates themselves.

While formula (1) is defined for a one-year period, it can be extended (approximately) to a multi-year period by replacing p = *proportion of smokers at year start* with p^* = *proportion of smokers at mid period*, so long as it is reasonable to assume constant r and m over the multi-year period. The shorter the multi-year period, typically the better the approximation.

The results of applying formula (1) to nine different test cases are presented in Figure 3. For example, in the first case, we model a 1 percent annual decline in smoking, a 30 percent smoking rate at year start, and a 2:1 smoker to non-smoker mortality ratio. For this test case, we calculate that the changing smoking rate alone will give rise to 23 basis points (bps) of population-level mortality improvement (per annum) over the period. Based on these test cases, we see that it is not unreasonable to expect smoking rate change-induced mortality improvements of 25, 50, or even 75 bps per annum, depending on the group under consideration.

Figure 3
Impact of a Changing Smoking Rate on Population-Level MI—Select Cases

Case	r	p	m	Population-Level MI from a Changing Smoking Rate (Per Annum)
1	–1%	30%	2	0.23%
2	–2%	30%	2	0.46%
3	–3%	30%	2	0.69%
4	–1%	20%	2	0.17%
5	–2%	20%	2	0.33%
6	–3%	20%	2	0.50%
7	–2%	10%	2	0.18%
8	–2%	20%	3	0.57%
9	–2%	30%	3	0.75%

These smoking rate change-induced impacts are indeed material given that overall mortality improvement rates (i.e., from all sources, including medical advances) are often estimated to be in the low single percentage digits. For example, if under Case

6, one estimated an overall population-level mortality improvement of 2 percent per annum, the smoking rate change-induced component alone would account for one-quarter of the overall rate. If the practitioner subsequently extrapolated the 2 percent per annum population-level estimate to (say) a group of nonsmokers, he/she would implicitly be carrying over 50 bps per annum of smoking rate change-induced mortality improvement, likely resulting in an overstatement of mortality improvement for the target group.

CONCLUSION

When estimating and setting mortality improvement assumptions, it is critical that the practitioner model only the relevant sources of mortality improvement for the intended application. As I have discussed in this article, a changing smoking rate alone can give rise to material population-level mortality improvement. To the extent that this smoking rate change-induced component of mortality improvement exists in the practitioner's study representation, it is important that he/she quantify its impact and determine how much of it, if any, should be reflected in the target application. ■

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ENDNOTES

1 Statistics Canada. *Table 105-0501*, April 22, 2016: *http://www5.statcan.gc.ca/cansim/a26?lang=eng&retrLang=eng&id=1050501&&pattern=&stByVal=1&p1=1&p2=37&tabMode=dataTable&csid=*

2 Jamal A, King BA, Neff LJ, Whitmill J, Babb SD, Graffunder CM. Current Cigarette Smoking Among Adults—United States, 2005–2015. MMWR Morb Mortal Wkly Rep 2016;65:1205–1211. DOI: *https://www.cdc.gov/mmwr/volumes/65/wr/mm6544a2.htm?s_cid=mm6544a2_w*

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 one of two. It has been formatted for the newsletter and is reprinted with permission from Deloitte Development LLC. Stay tuned for Deloitte's next release on predictive modeling, which will include some newer concepts and solutions such as Electronic Health Records and Behavioral Health.

THE RISE OF "ANALYTIC" DECISION MAKING

Predictive modeling can be defined as the analysis of large data sets to make inferences or identify meaningful relationships, and the use of these relationships to better predict future events [1,2]. It uses statistical tools to separate systematic patterns from random noise, and turns this information into business rules, which should lead to better decision making. In a sense, this is a discipline that actuaries have practiced for quite a long time. Indeed, one of the oldest examples of statistical analysis guiding business decisions is the use of mortality tables to price annuities and life insurance policies (which originated in the work of John Graunt and Edmund Halley in the 17th century). Likewise, throughout much of the 20th century, general insurance actuaries have either implicitly or explicitly used Generalized Linear Models [3,4,5] and Empirical Bayes (a.k.a. credibility) techniques [6,7] for the pricing of short-term insurance policies. Therefore, predictive models are in a sense, "old news." Yet in recent years, the power of statistical analysis for solving business problems and improving business processes has entered popular consciousness and become a fixture in the business press. "Analytics," as the field has come to be known, now takes on a striking variety of forms in an impressive array of business and other domains.

Credit scoring is the classic example of predictive modeling in the modern sense of "business analytics." Credit scores were initially developed to more accurately and economically underwrite and determine interest rates for home loans. Personal auto and home insurers subsequently began using credit scores to improve their selection and pricing of personal auto and home risks [8,9]. It is worth noting that one of the more significant analytical innovations in personal property-casualty insurance in recent decades originated outside the actuarial disciplines. Still more recently, U.S. insurers have widely adopted scoring models—often containing commercial credit information—for pricing and underwriting complex and heterogeneous commercial insurance risks [10].

The use of credit and other scoring models represents a subtle shift in actuarial practice. This shift has two related aspects. First, credit data is behavioral in nature and, unlike most traditional rating variables, bears no direct causal relationship to insurance losses. Rather, it most likely serves as a proxy measure for non-observable, latent variables such as "risk-seeking temperament" or "careful personality" that are not captured by more traditional insurance rating dimensions. From here it is a natural leap to consider other sources of external information, such as lifestyle, purchasing, household, social network, and environmental data, likely to be useful for making actuarial predictions [11, 24].

Second, the use of credit and other scoring models has served as an early example of a widening domain for predictive models in insurance. It is certainly natural for actuaries to employ modern analytical and predictive modeling techniques to arrive at better solutions to traditional actuarial problems such as estimating mortality, setting loss reserves, and establishing classification ratemaking schemes. But actuaries and other insurance analytics are increasingly using predictive modeling techniques to improve business processes that traditionally have been largely in the purview of human experts.

For example, the classification ratemaking paradigm for pricing insurance is of limited applicability for the pricing of commercial insurance policies. Commercial insurance pricing has traditionally been driven more by underwriting judgment than by actuarial data analysis. This is because commercial policies are few in number relative to personal insurance policies, are more heterogeneous, and are described by fewer straightforward rating dimensions. Here, the scoring model paradigm is especially useful. In recent years it has become common for scoring models containing a large number of commercial credit and non-credit variables to ground the underwriting and pricing process more in actuarial analysis of data, and less in the vagaries of expert judgment. To be sure, expert underwriters remain integral to the process, but scoring models replace the blunt instrument of table- and judgment-driven credits and debits with the precision tool of modeled conditional expectations.

Similarly, insurers have begun to turn to predictive models for scientific guidance of expert decisions in areas such as claims management, fraud detection, premium audit, target marketing, cross-selling, and agency recruiting and placement. In short, the modern paradigm of predictive modeling has made possible a broadening, as well as a deepening, of actuarial work.

As in actuarial science, so in the larger worlds of business, education, medicine, sports, and entertainment. Predictive modeling techniques have been effective in a strikingly diverse array of applications such as:

- Predicting criminal recidivism [12] Making psychological diagnoses [12]
- Helping emergency room physicians more effectively triage patients [13] Selecting players for professional sports teams [14]
- Forecasting the auction price of Bordeaux wine vintages [15]
- Estimating the walk-away "pain points" of gamblers at Las Vegas casinos to guide casino personnel who intervene with free meal coupons [15]
- Forecasting the box office returns of Hollywood movies [16]

A common theme runs through both these and the above insurance applications of predictive modeling. Namely, in each case predictive models have been effective in domains traditionally thought to be in the sole purview of human experts. Such findings are often met with surprise and even disbelief.

Psychologists, emergency room physicians, wine critics, baseball scouts, and indeed insurance underwriters are often and understandably surprised at the seemingly uncanny power of predictive models to outperform unaided expert judgment. Nevertheless, substantial academic research, predating the recent enthusiasm for business analytics by many decades, underpins these findings. Paul Meehl, the seminal figure in the study of statistical versus clinical prediction, summed up his life's work thus [17]:

> There is no controversy in social science which shows such a large body of quantitatively diverse studies coming out so uniformly in the same direction as this one. When you are pushing over 100 investigations, predicting everything from the outcome of football games to the diagnosis of liver disease, and when you can hardly come up with half a dozen studies showing even a weak tendency in favor of the clinician, it is time to draw a practical conclusion.

Certainly not all applications of predictive modeling have a "clinical versus actuarial judgment" character [18]. For example, amazon.com and netflix.com make book and movie recommendations without any human intervention [25]. Similarly, the elasticity-optimized pricing of personal auto insurance policies can be completely automated (barring regulatory restrictions) through the use of statistical algorithms. Applications such as these are clearly in the domain of machine, rather than human, learning. However, when seeking out ways to improve business processes, it is important to be cognizant of the often surprising ability of predictive models to improve judgment-driven decision-making.

CURRENT STATE OF LIFE INSURANCE PREDICTIVE MODELING

While life insurers are noted among the early users of statistics and data analysis, they are absent from the above list of businesses where statistical algorithms have been used to improve expert-driven decisions processes. Still, early applications of predictive modeling in life insurance are beginning to bear fruit, and we foresee a robust future in the industry [19].

Life insurance buffers society from the full effects of our uncertain mortality. Firms compete with each other in part based on their ability to replace that uncertainty with (in aggregate) remarkably accurate estimates of life expectancy. Years of fine-tuning these estimates have resulted in actuarial tables that mirror aggregate insured population mortality, while underwriting techniques assess the relative risk of an individual. These methods produce relatively reliable risk selection, and as a result have been accepted in broadly similar fashion across the industry. Nonetheless, standard life insurance underwriting techniques are still quite costly and time consuming. A life insurer will typically spend approximately one month and several hundred dollars underwriting each applicant.[1]

Many marginal improvements to the underwriting process have taken hold: simplified applications for smaller face amounts, refinement of underwriting requirements based upon protective value studies, and streamlined data processing via automated software packages are all examples. However, the examples in the previous section suggest that property-casualty insurers have gone farther in developing analytics-based approaches to underwriting that make better use of available information to yield more accurate, consistent, and efficient decision-making. Based on our experience, life insurance underwriting is also ripe for this revolution in business intelligence and predictive analytics. Perhaps motivated by the success of analytics in other industries, life insurers are now beginning to explore the possibilities.[2]

Despite our enthusiasm, we recognize that life underwriting presents its own unique set of modeling challenges which have made it a less obvious candidate for predictive analytics. To illustrate these challenges it is useful to compare auto underwriting, where predictive modeling has achieved remarkable success, with life underwriting, where modeling is a recent entry. Imagine everything an insurer could learn about a prospective customer: age, type of car, accident history, credit history, geographic location, personal and family medical history, behavioral risk factors, and so on. A predictive model provides a mapping of all these factors combine onto the expected cost of insuring the customer. Producing this map has several prerequisites:

- A clearly defined target variable, i.e., what the model is trying to predict
- The availability of a suitably rich data set, in which at least some predictive variables correlated with the target can be identified
- A large number of observations upon which to build the model, allowing the abiding relationships to surface and be separated from random noise
- An application by which model results are translated into business actions

While these requirements are satisfied with relative ease in our auto insurance example, life insurers may struggle with several of them.

	Auto Insurer	Life Insurer
Target Variable	Claims over six-month contract	Mortality experience over life of product (10, 20+ years)
Modeling Data	Underwriting requirements supplemented by third-party data	Underwriting requirements supplemented by third-party data
Frequency of Loss	Approximately 10 percent of drivers make claims annually	Typically, fewer than 1 first year death per 1,000 new policies issued
Business Action	Underwriting Decision	Underwriting Decision

Statisticians in either domain can use underwriting requirements, which are selected based upon their association with insurance risk, supplement them with additional external data sources, and develop predictive models that will inform their underwriting decisions. However, the target variable and volume of data required for life insurance models raise practical concerns.

For the auto insurer, the amount of insurance loss over the six-month contract is an obvious candidate for a model's target variable. But because most life insurance is sold through long duration contracts, the analogous target variable is mortality experience over a period of 10, 20, or often many more years. Because the contribution of a given risk factor to mortality may change over time, it is insufficient to analyze mortality experience over a short time horizon. Further, auto insurers can correct underwriting mistakes through rate increases in subsequent policy renewals, whereas life insurers must price appropriately from the outset.

We recognize that life underwriting presents its own unique set of modeling challenges.

The low frequency of life insurance claims (which is good news in all other respects) also presents a challenge to modelers seeking to break ground in the industry. Modeling statistically significant variation in either auto claims or mortality requires a large sample of loss events. But whereas approximately 10 percent of drivers will make a claim in a given year, providing an ample data set, life insurers can typically expect less than one death in the first year of every 1,000 policies issued.[3] Auto insurers can therefore build robust models using loss data from the most recent years of experience, while life insurers will most likely find the data afforded by a similar time frame insufficient for modeling mortality.

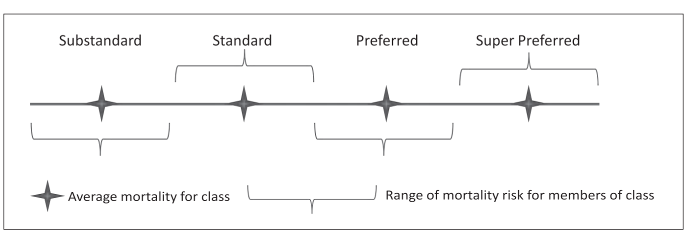
The low frequency of death and importance of monitoring mortality experience over time leaves statisticians looking for life insurance modeling data that spans many (possibly 20) years. Ideally this would be a minor impediment, but in practice, accessing usable historical data in the life insurance industry is often a significant challenge. Even today, not all life insurers capture underwriting data in an electronic, machine-readable format. Many of those that do have such data only implemented the process in recent years. Even when underwriting data capture has been in place for years, the contents of the older data (i.e., which requirements were ordered) may be very different from the data gathered for current applicants.

These challenges do not preclude the possibility of using predictive modeling to produce refined estimates of mortality. However, in the short term they have motivated a small, but growing number of insurers to begin working with a closely related yet more immediately feasible modeling target: the underwriting decision on a newly issued policy. Modeling underwriting decisions rather than mortality offers the crucial advantage that underwriting decisions provide informative short term feedback in high volumes. Virtually every application received by a life insurer will have an underwriting decision rendered within several months. Further, based upon both historical insurer experience and medical expertise, the underwriting process is designed to gather all cost-effective information available about an applicant's risk and translate it into a best estimate of future expected mortality. Therefore, using the underwriting decision as the target variable addresses both key concerns that hinder mortality- predicting models.

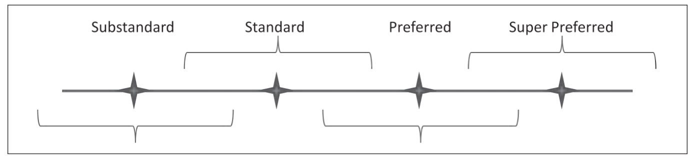
Of course, underwriting decisions are imperfect proxies for future mortality. First, life underwriting is subject to the idiosyncrasies, inconsistencies, and psychological biases of human decision-making.

Indeed this is a major motivation for bringing predictive models to bear in this domain. But do these idiosyncrasies and inconsistencies invalidate underwriting decisions as a candidate target variable? No. To the extent that individual underwriters' decisions are independent of one another and are not affected by common biases, their individual shortcomings tend to "diversify away." A famous example illustrates this concept. When Francis Galton analyzed 787 guesses of the weight of an ox from a contest at a county fair, he found that the errors of the individual guesses essentially offset one another, and their average came within one pound of the true weight of the ox. This illustrates how regression and other types of predictive models provide a powerful tool for separating "signal" from "noise."

In fact, the Galton example is quite similar to how life insurers manage mortality. Although individual mortality risk in fact falls along a continuum, insurers group policyholders into discrete underwriting classes and treat each member as if they are of average risk for that class. When the risks are segmented sufficiently, insurers are able to adequately price for the aggregate mortality risk of each class.



However, to avoid anti-selection and maintain the integrity of the risk pools insurers must segment risks into classes that are homogenous. While the "noise" in underwriting offers may diversify, these offers are accepted or rejected by applicants strategically. On average, applicants who have knowledge of their own health statuses will be more likely to accept offers that are in their favor, and reject those that are disadvantageous. For example, in the figure below an applicant at the upper range of the standard class may qualify for preferred with another insurer, thus leaving the risk profile of the original standard class worse than expected.



Therefore, anything that widens the range of mortality risks in each class, and thus blurs the lines between them, poses a threat to a life insurer. In addition to the inconsistency of human decision making, global bias resulting from company-wide underwriting guidelines that may not perfectly represent expected mortality can also contribute to this potential problem.

While modeling underwriting decisions may ultimately become a step along the path towards modeling mortality directly, we do believe today it is a pragmatic approach that provides the maximal return on modeling investment today. Specifically, utilizing underwriting decisions as the target variable is advantageous because they are in generous supply, contain a great deal of information and expert judgment, and do not require long "development" periods as do insurance claims. At the same time they contain diversifiable "noise" that can be dampened through the use of predictive modeling. Although building models for mortality and improving risk segmentation remain future objectives, utilizing predictive models based upon historical underwriting decisions represents a significant improvement on current practice, and is a practical alternative in the common scenario where mortality data is not available in sufficient quantities for modeling.

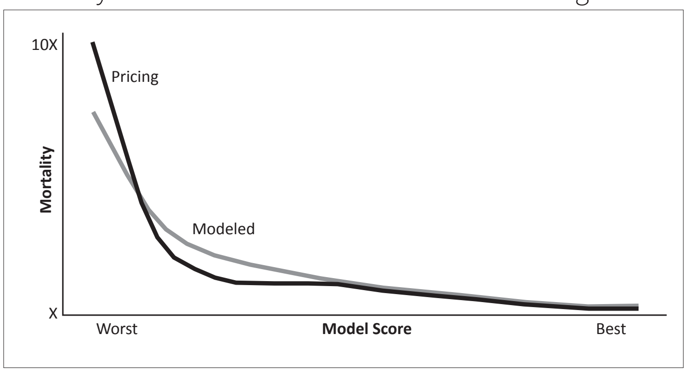
BUSINESS APPLICATION THAT CAN HELP DELIVER A COMPETITIVE ADVANTAGE

We will describe the technical aspects of underwriting predictive models in some detail in a subsequent section. While that discussion may beguile certain members of the audience (the authors included), others will be more interested in understanding how predictive modeling can deliver a competitive advantage to life insurers.

Life Underwriting

Unsurprisingly, one compelling application has been to leverage models that predict underwriting decisions directly within the underwriting process. As mentioned above, underwriting is a very costly and time consuming, but necessary, exercise for direct life insurance writers. Simply put, the underwriting process can be made faster, more economical, more efficient, and more consistent when a predictive model is used to analyze a limited set of underwriting requirements and inexpensive third-party marketing data sources (both described below) to provide an early glimpse of the likely underwriting result. As illustrated in Figure 1, the underwriting predictive models that Deloitte has helped insurers develop have been able to essentially match the expected mortality for many applicants. These insurers are beginning to leverage model results to issue many of their policies in just several days, thus foregoing the more costly, time consuming, and invasive underwriting requirements.

Figure 1
Mortality of Predictive Model vs. Full Underwriting



Risks which had been underwritten by the insurer and kept in a holdout sample were rank-ordered by model score and divided into equal-sized deciles. Modeled mortality is computed by taking a weighted average of the insurer's mortality estimates for each actual underwriting class in proportion to their representation within each decile. Pricing mortality represents the fully underwriting pricing mortality assumptions.

Issuing more policies with fewer requirements may initially seem like a radical change in underwriting practices, but we think of it as an expansion of a protective value study. Just as insurers currently must judge when to begin ordering lab tests, medical exams records, and EKGs, the models are designed to identify which applicant profiles do and do not justify the cost of these additional requirements. Based on the results of the models we've helped insurers build thus far, the additional insight they provide has allowed these insurers to significantly change the bar on when additional tests are likely to reveal latent risk factors. As indicated by the quality of fit between the model mortality and pricing assumptions, these models have been able to identify approximately 30 percent to 50 percent of the applicants that can be issued policies through a streamlined process, and thus avoid the traditional requirements.

With impressive frequency, the underwriting decision recommended by these models matched the decision produced through full underwriting. For cases when they disagree, however, we offer two possibilities: 1) the models do not have access to information contained in the more expensive requirements which may provide reason to change the decision, or 2) models are not subject to biases or bounded cognition in the same way that underwriters, who do not always act with perfect consistency or optimally weigh disparate pieces of evidence, are. The latter possibility comports with Paul Meehl's and his colleagues' studies of the superiority of statistical over clinical decision making, and is further motivation for augmenting human decision-making processes with algorithmic support.

In our analyses of discrepancies between models and underwriting decisions we did encounter cases where additional underwriting inputs provided valuable results, but they were rivaled by instances of underwriting inconsistency. When implementing a model, business rules are used to capitalize upon the model's ability to smooth inconsistency, and channel cases where requirements are likely to be of value to the traditional underwriting process. Thus, our experience therefore suggests that insurance underwriting can be added to the Meehl school's long list of domains where decision-making can be materially improved through the use of models.

These results point to potentially significant cost savings for life insurers. Based on a typical company's volume, the annual savings from reduced requirements and processing time are in the millions, easily justifying the cost of model development. Table 1 shows a rough example of the potential annual savings for a representative life insurer. It lists standard underwriting requirements and roughly typical costs and frequencies with which they would be ordered in both a traditional and a model-enhanced underwriting process. It then draws a comparison between the costs of underwriting using both methods.

Table 1
Illustrative Underwriting Savings from Predictive Model

	Requirement Cost	Requirement Utilization	
		Traditional Underwriting	Predictive Model
Paramedical Exam	$55	50%	0%
Oral Fluids Analysis	$25	20%	0%
Blood and Urine Analysis	$55	70%	0%
MVR Report	$6	70%	75%
Attending Physician Statement	$100	20%	0%
Medical Exam	$120	20%	0%
EKG	$75	10%	0%
Stress Test	$450	1%	0%
Third-Party Data	$0.50	0%	100%
Total Cost Per Applicant		**$130**	**$5**
Savings Per Applicant		**$125**	
Annual Applications Received		**50,000**	
Annual Savings (over 30% to 50% of applications)		**$2 to $3 million**	

In addition to hard dollars saved, using a predictive model in underwriting can generate opportunities for meaningful improvements in efficiency and productivity. For example, predictive modeling can shorten and reduce the invasiveness of the underwriting. The time and expense required to underwrite an application for life insurance and make an offer is an investment in ensuring that risks are engaged at an appropriate price. However, the effort associated with the underwriting process can be considered a deterrent to purchasing life insurance. Resources spent while developing a lead, submitting an application, and underwriting a customer who does not ultimately purchase a policy are wasted from the perspective of both the producer and home office. The longer that process lasts, and the more tests the applicant must endure, the more opportunity the applicant has to become frustrated and abort the purchase entirely, or receive an offer from a competitor. Further, complications with the underwriting process also provide a disincentive for an independent producer to bring an applicant to a given insurer. Enhancing underwriting efficiency with a model can potentially help life insurers generate more applications, and place a higher fraction of those they do receive. In addition, the underwriting staff, which is becoming an increasingly scarce resource,[4] will be better able to handle larger volumes as more routine work is being completed by the model.

We should emphasize that we do not propose predictive models as replacements for underwriters. Underwriters make indispensable contributions, most notably for applicants where medical tests are likely to reveal risk factors requiring careful consideration. Ideally, models could be used to identify the higher risk applicants early in the underwriting process, streamline the experience for more straightforward risks, and thus free up the underwriter's time for analysis of the complex risks. In addition, underwriters can and should provide insight during the construction, evaluation, and future refinements of predictive models. This is an oft overlooked but significant point. Particularly in complex domains such as insurance, superior models result when the analyst works in collaboration with the experts for whom the models are intended.

How exactly does the process work? The rough sequence is that the insurer receives an application, then a predictive model score is calculated, then a policy is either offered or sent through traditional underwriting. In more detail, the predictive model is typically used not to make the underwriting decisions, but rather to triage applications and suggest whether additional requirements are needed before making an offer. To that end, the model takes in information from any source that is available in near-real time for a given applicant. This can include third-party marketing data and more traditional underwriting data such as the application/tele-interview, MIB, MVR, and electronic prescription database records. For most insurers, this data can be obtained within two days of receiving the application.[5]

We should point out one key change some insurers must endure. It is essential that producers do not order traditional requirements at the time an application is taken. If all requirements are ordered immediately at the application, eliminating them based upon model results is impossible. For some insurers, this is a major process change for the producer group.

After loading the necessary data for model inputs, the model algorithm runs and produces a score for the application. From here, several approaches can lead to an underwriting decision. One central issue insurers may wrestle with is how to use the model output when justifying an adverse action (i.e., not offering an individual applicant the lowest premium rate). Due to regulatory requirements and industry conventions, it is customary to explain to applicants and producers the specific reasons in cases where the best rates are not offered. It is possible to fashion a reason message algorithm that "decomposes" the model score into a set of intuitively meaningful messages that convey the various high-level factors pushing an individual score in a positive or negative direction. There is considerable latitude in the details of the reason message algorithm, as well as the wording of the messages themselves.

While allowing the model algorithm to place applicants in lower underwriting classes while delivering reason codes is a viable, given the novelty of using predictive modeling in underwriting, the approach life insurers have been most comfortable with thus far is underwriting triage. That is, allowing the model to judge which cases require further underwriting tests and analysis, and which can be issued immediately. From a business application perspective, the central model implementation question then becomes: what model score qualifies an applicant for the best underwriting class that would otherwise be available based upon existing underwriting guidelines? The information contained in the application and initial requirements will set a ceiling upon the best class available for that policy. For example, let us assume an insurer has set an underwriting criterion that says children of parents with heart disease cannot qualify for super preferred rates. Then for applicants that disclose parents with this condition on the application, a model can recommend an offer at preferred rates without taking the decisive step in the disqualification from super preferred.

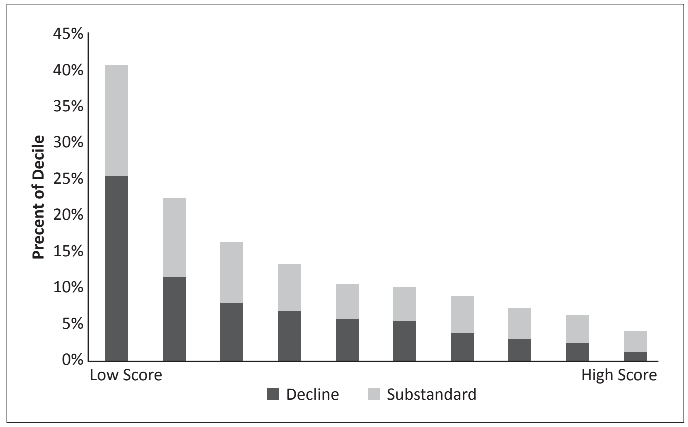
That is, the role of the model is to determine whether an applicant's risk score is similar enough to other applicants who were offered preferred after full underwriting. If so, the insurer can offer preferred to this applicant knowing the chance that additional requirements will reveal grounds for a further downgrade (the protective value) will be too small to justify their cost. If the applicant's risk score is not comparable to other preferred applicants, the insurer can continue with the traditional underwriting.

Marketing

In addition to making the underwriting process more efficient, modeling underwriting decisions can be of assistance in selling life insurance by identifying potential customers who are more likely to qualify for life insurance products. Marketing expenses are significant portions of life insurance company budgets, and utilizing them efficiently is a key operational strategy. For example, a company may have a pool of potential customers, but know little about their health risks at the individual level. Spreading the marketing efforts evenly over the pool will yield applicants with average health. However, this company could likely increase sales by focusing marketing resources on the most qualified customers.

The models supporting underwriting decisions that we have discussed thus far leverage both third-party marketing data and a limited set of traditional underwriting requirements. Alternatively, we can build predictive models using only the marketing data. While these marketing models do not deliver the same predictive power as those that utilize traditional underwriting data, they still segment risks well enough to inform direct marketing campaigns. Scoring the entire marketing pool and employing a targeted approach should help reduce the dollars spent marketing to those who will later be declined or less likely to accept an expensive offer, and result in an applicant pool that contains more healthy lives.

Figure 2
Marketing Model Segmentation



Like Figure 1, risks which had been underwritten by the insurer and kept in a holdout sample were rank-ordered by model score (using third-party data only) and divided into equal-sized deciles. However, this graph shows fractions of those deciles which contain declined or substandard applicants.

In addition to general target marketing efforts, models of underwriting decisions can also serve more specific sales campaigns. For example, multiline insurers, or even broader financial institutions often attempt to increase sales by cross-marketing life products to existing customers. However, they run the risk of alienating a current customer if the post-underwriting offer is worse than what the marketing suggests. Instead of selling an additional product, the company may be at risk of losing the customer. In dealing with this challenge, predictive modeling can be used to conduct an initial review of the customer pool and assist in determining which existing customers should receive offers for life insurance.

Predictive modeling can also aid in targeting specific products to the markets for which they were designed. For example, a given company may sell a product with preferred rates that are competitive, but standard rates that are less attractive. Other products may contain incentives for the insured to maintain healthy lifestyle. To whom might these products appeal? A person who the model indicates is currently living a healthy lifestyle is a prime target for such marketing programs.

In-Force Management

It is well known that the effects of underwriting wear off over time. Lives that were initially healthy may have degraded, and people who appeared to be poor risks initially may have improved. Products are priced to anticipate a reversion to mean health risk, but considerable variation in the health status of in-force policyholders will both remain and be unobservable without new underwriting. While full underwriting is cost prohibitive in these situations, a predictive model could be an inexpensive and transparent alternative. Scoring the in-force block could provide more insight to emerging mortality experience, inform changes to nonguaranteed policy features, help insurers know where to focus efforts to retain policyholders, and guide both direct writers and reinsurers in block transactions.

Additional Predictive Model Applications

We have focused our discussion on modeling health risk for life insurers because it is arguably the latest advancement, but there are many other areas of uncertainty for life insurers where a predictive model could reveal valuable information. We will present several potential applications in brief.

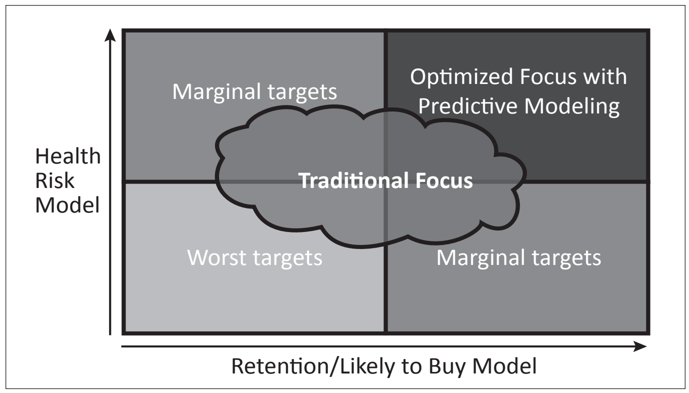
Analogous to models used to market consumer products, predictive algorithms can also estimate how interested a potential customer would be in purchasing a product from a life insurance company.

Insurance customers are often relatively affluent, or have recently undergone life-changing events such as getting married, having children, or purchasing a house. All of these traits and events (among other characteristics) can be identified in the marketing data. More specifically, a predictive model can be built to identify which characteristics are most highly correlated with the purchase of life insurance.

Again, scoring a direct marketing database can help a life insurer determine where to focus limited resources for marketing and sales.

We have discussed retention in terms of which customers an insurer would most like to keep, but equally important is which customers are most likely to leave. As many of the same life event and lifestyle indicators in the marketing data communicate when a person is likely to purchase a product, they also hint when a person is likely to surrender a product. In addition to third-party data, insurers also can see indicators of impending surrenders in transactional data such as how policyholders are paying premiums (automatic bank debits vs. having to physically write each year, or month), whether a policyholder is taking policy loans, whether they are calling the home office asking for cash values, account balances, and in-force illustrations, etc. Since neither producers nor the home office can give complete attention to each policyholder, a predictive model can sort these different indicators and help prioritize where to focus policy-saving effort.

Predictive modeling becomes even more powerful when models are used in combination. Not only can they answer who is most likely to purchase or surrender, but they can simultaneously identify the customers the company would most like to insure. Layering the underwriting health risk model on top of either the purchase or surrender models will tell the insurer which quadrant of the population will likely yield the highest return.



A final application we will mention is workforce analytics. Becoming a successful life insurance agent is notoriously difficult. The home office spends significant resources recruiting and training these agents, and the high turnover rate is a considerable drain. Predictive models can be used to help improve the efficiency of agent recruiting by scoring applicants on the basis of how similar their profile is to that of a company's existing successful field force. Such a tool can help prioritize which applicants to pursue.

When considering all the potential applications for predictive modeling in life insurance, it becomes apparent that analytics is truly an enterprise capability rather than a niche solution. After an insurer begins with one application that proves successful, the next application follows more easily than the first. Expertise, data, and infrastructure can be leveraged throughout the organization, but more importantly, decision makers come to realize and respect the power of predictive modeling.

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ENDNOTES

1 According to the Deloitte 2008 LIONS benchmarking study of 15 life insurers, the median service time to issue a new policy ranges between 30 and 35 days for policies with face amounts between $100k to $5 million, and the average cost of requirements (excluding underwriter time) is $130 per applicant.

2 As reported in an SOA sponsored 2009 study, "Automated Life Underwriting," only 1 percent of North American life insurers surveyed are currently utilizing predictive modeling in their underwriting process.

3 This is an estimate based upon industry mortality tables. Mortality experience varies across companies with insured population demographics. In the 2001 CSO table, the first-year select, weighted average mortality rate (across gender and smoker status) first exceeds 1 death per thousand at age 45.

4 According to the Bureau of Labor Statistics 2010-2011 Occupational Outlook Handbook, despite reduced employment due to increased automation, the job outlook of insurance underwriters is classified as "good" because "the need to replace workers who retire or transfer to another occupation will create many job openings."

5 Receiving the application is defined as when all application questions have been answered and/or the tele- interview has been conducted. If applicable, this includes the medical supplement portion of the application.

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Highlights of Sessions at the 2017 SOA Annual Meeting & Exhibit

By Kurt A. Guske, Donna Megregian and John Timmerberg

This article contains a summary of some of the Product Development Section presentations given at the 2017 SOA Annual Meeting & Exhibit in Boston this past October. Thanks to Donna Megregian and John Timmerberg for their session contributions. You can also find session presentations on the SOA website as well as virtual sessions at https://www.soa.org/prof-dev/events/2017/annual-meeting/virtual-session/. *We encourage everyone to join our LinkedIn group where you can participate in discussions on these or any other topics that are relevant to our business. If you would like to present at an upcoming SOA event or write an article for* Product Matters!, *please contact Lindsay Meisinger at* lmeisinger@rgare.com, *Simpa Baiye at* simpa.baiye@pwc.com, *Blake Hill at* Blake_Hill@manulife.com, *or me at* kurt.guske@aig.com.

SESSION 87: NEW OPPORTUNITIES IN ACCELERATED BENEFIT RIDERS

Moderator: John Leo Timmerberg, ASA, MAAA; Presenters: Jeanne Meeker Daharsh, FSA, MAAA, and Denise Liston

More than 150 actuaries attended session 87, New Opportunities in Accelerated Benefit Riders, at the 2017 SOA Annual Meeting. John L. Timmerberg, ASA, MAAA, consulting actuary with Accelerated Actuarial began the session with an introduction to the accelerated benefit rider types (chronic illness, critical illness and terminal illness), rider structures, and the size and growth of the market. He discussed the pros and cons of the three rider structures (full benefit, fractional benefit and lien), the relative value to the policyholder and the pricing risks of each structure. Special pricing considerations for combining the riders with the various base life products were discussed.

Denise Liston, vice president at LifePlans, Inc., continued the session with underwriting considerations for these riders. Denise discussed the underwriting risks for chronic and critical illness accelerated benefit riders, including IADLs (instrumental activities of daily living) and ADLs (activities of daily living) and their impact on the rider benefit triggers. She explained IADLs as precursors such as forgetting medications, inability to use telephone or prepare meals, for example. She included additional emphasis on cognitive and dementia risks and how these impact the underwriting for chronic illness accelerated benefit riders.

Jeanne Daharsh, FSA, MAAA, actuarial reviewer for the Interstate Insurance Product Regulation Commission (IIPRC), outlined the benefits of filing new products with the IIPRC and the scope and volume of filings approved. She discussed how the IIPRC reviews these rider filings and tips for avoiding common filing pitfalls. For example, coverage has to be incidental to the life coverage which means less than 10 percent of the life event. She explained that the average time to approval is 26 days through the Compact.

The session concluded with a lively question and answer session.

SESSION 29: TOOLS AND DATA IN UNDERWRITING PROCESS

Moderator: Donna Christine Megregian, FSA, MAAA; Presenters: Donna Christine Megregian, FSA, MAAA, Kevin Pledge, FSA, FIA, and Zhe (David) Zhu, FSA, FCIA, Ph.D.

Companies are looking for ways to improve the customer experience during the sales process. Beyond the traditional sources of underwriting, speakers in this session discussed newer sources of information such as facial recognition, electronic health records, credit, and mortality risk scores. Presenters talked about some validation studies with both positive and negative results. They also discussed considerations companies should think through as they adopt the new tools, such as regulatory, consumer, and

administrative issues. For example, be cognizant of unintended unfair discrimination in establishing these new programs and processes. Another key example is messaging that triage is a path to a noninvasive underwriting process and not a decision, which is paramount to using these newer information sources in the triage process. Transparency and disclosure are becoming key consumer and regulatory issues while adjustments to systems and proper tracking and monitoring are key company issues to manage.

SESSION 161: BEST PRACTICES & CONSIDERATIONS FOR ACCELERATED UNDERWRITING

Moderator: Donna Christine Megregian, FSA, MAAA; Presenters: Gregory A. Brandner, FSA, MAAA, and Lisa Hollenbeck Renetzky, FSA, MAAA

So many companies are implementing accelerated underwriting programs which many may find difficult to define. The panelists discussed ways, with audience voting participation, to put accelerated underwriting and simplified issue closer to fully underwritten mortality as many companies do not want to modify retail rates significantly to accommodate the process.

Points discussed included should the program just go to age fifty? What target markets would be optimal? Should age and amount grid vary by age? What products make sense? The panel claimed most often seeing programs on term. An audience survey revealed the session participant companies are more often using MIB, MBR, Rx, and credit/credit-based scores as data sources in their accelerated underwriting processes than industry or proprietary predictive models.

A few things the panel discussed included how companies are implementing accelerated underwriting programs (what ways and which products), timelines to implement an accelerated underwriting program, and what areas need to be involved in the process. An audience survey revealed seventy-five percent of the session participants believe creating and implementing an accelerated underwriting program will take at least nine months. Forty-one percent think it will be longer than twelve months.

It's important to monitor the accelerated underwriting program. One way to do this is by using a misclassification matrix to map the results of the program versus how they would be fully underwritten.

And what's in store for the future in risk selection? The panelists' prediction is more individualized mortality scores.

SESSION 118: VM-20 IMPACT ON PRODUCT DEVELOPMENT: RESEARCH STUDY PHASE 2

Moderator: Kelly J. Rabin, FSA, MAAA; Presenters: Paul Fedchak, FSA, MAAA, Jacqueline M. Keating, FSA, MAAA, and Michael W. Santore, FSA, MAAA

The panel presented results of the second phase of the SOA sponsored research of the impact of VM-20 on term and ULSG product designs. They analyzed the impacts to the net premium reserve (NPR), deterministic reserve (DR), and stochastic reserve (SR) under a variety of different case studies. The presentation opened with a brief summary of phase 1 results, upon which the phase 2 case studies were built.

Photo by Hyon Smith.

The phase 1 results showed that on term, the NPR floor was the winner in early level premium term (twenty year) durations. The DR is slightly higher in the tail end of the level premium period. On ULSG with no-lapse premium to attained age 110, the DR exceeded the NPR in all durations. The SR excess is small and limited to early durations.

Companies currently engaged in reserve financing would yield lower profits under VM-20, according to the study. Term without financing experienced more favorable results with VM-20 than under CRVM reserves. ULSG with and without financing experienced less favorable results in the VM-20 study than with CRVM.

The panel also discussed the impact of different assumptions on the deterministic reserves to understand each assumption's attribution to the total reserve. According to the study, removing the mortality margins had a notable impact, while removing expense margin and lapse margins had smaller reductions to the DR. Removing all appeared to converge with the baseline where the DR exceeded the NPR, at the tail end of the level premium period.

The mortality margin is a key driver of the overall deterministic reserve. As a result, the ability to forecast the DR with updated mortality improvement up to the valuation date is important.

The phase 2 case studies focused on small company, simplified-issue term, coinsurance, 30-year level term, and short pay ULSG situations. Each study began from phase 1 results and layered in assumption changes to examine the impact on VM-20 reserves and pricing results. For instance, the small company study demonstrated that coinsurance is effective on UL with lower credibility and longer duration liabilities, and less effective on term.

The panel also discussed the industry interviews that were conducted and summarized as part of the phase 2 study. The topics covered in the interviews included industry preparedness for VM-20, implementation concerns, collaboration, and the pricing process.

More details of the research can be found at the SOA website at *https://www.soa.org/research-reports/2016/2016-impact-of-vm20-product-development/*.

SESSION 174: NEWLY PROPOSED ASOPS: PRICING, MODELING, AND SETTING ASSUMPTIONS

Moderator: David C. Armstrong, FSA, MAAA; Presenters: Nick Fiechter, FSA, MAAA, Maria Rose Itteilag, and Donna Christine Megregian, FSA, MAAA

Did you know there were some newly proposed ASOPs that relate to the product development actuary? Although these are not yet final, the proposed ASOPs try to represent current practices and guidance which may help the actuary through the various product development exercises encountered. Presenters in this session went through each proposed ASOP's background and framework, then moved into scenarios where an actuary may be challenged to do the job being asked but may end up conflicting with or may be unclear with what is in the proposed ASOPs.

Most people at this session had not read the ASOPs. The panel stressed reviewing and commenting on the proposed ASOPs to ensure that clarity in guidance is achieved and enhancements have a chance to be included.

SESSION 188: INFORCE MANAGEMENT: UNDERSTANDING AND INCREASING ITS VALUE

Moderator: Donna Christine Megregian, FSA, MAAA; Presenters: Andy Ferris, FSA, FCA, MAAA, Stephanie J. Koch, FSA, MAAA, and Jennifer L. McGinnis, FSA, CERA, MAAA

The panel discussed the importance of doing inforce management and building an inforce management team. The panel shared some experience of building a team, developing goals and measuring success. The panel also discussed some cases where changes made have a potentially large impact on inforce values such as through post level term management.

Many companies are contemplating varying levels of nonguaranteed element changes as well, and these changes may be impacted by regulations like NY regulation 210. In the end, there are a variety of resources available for actuaries including Actuarial Standards of Practice 2, 12, 15, 24, and 33, along with proposed ASOPs on pricing, setting assumptions, and modeling from session 174. ■

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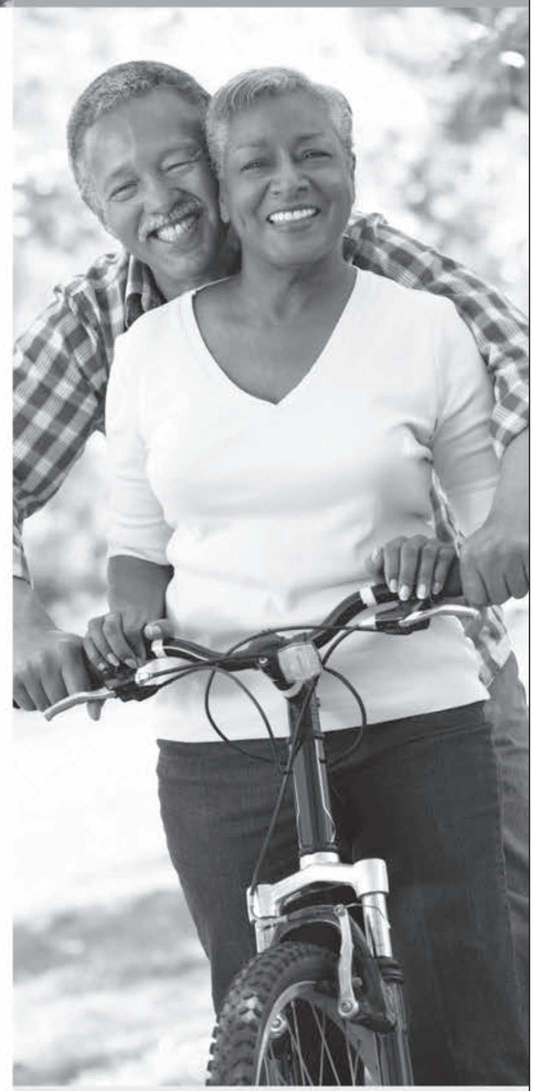
Call for Papers

The Committee on Living to 100 Research Symposia requests professionals, knowledgeable in the important area of longevity and its consequences, to prepare a high-quality paper for the 2020 Living to 100 Symposium in Orlando, FL. Topics of interest include, but are not limited to:

- Understanding the issues of mortality, longevity, morbidity and the quality of life;
- Models, techniques and data sources for mortality, morbidity, quality of life measurement and projection;
- Implications for society, institutions and individuals, as well as changes needed to support a growing aging population;
- Management of longevity risk by society, institutions and individuals; and
- Applications of existing or new longevity techniques, theories or methods for actuarial practice.

Please submit an abstract or outline of your proposed paper by Aug. 30, 2018. Abstracts should include a brief description of the topic, data sources and methods to be used, key items to be covered, and how your paper will contribute to current knowledge, theory and/or methodology. A brief curriculum vitae or resume is also required.

Submit the information by email to Jan Schuh, Sr. Research Administrator, at *jschuh@soa.org*.



Learn more about the call for papers, including the complete topic list, by going to *Livingto100.SOA.org*.

Questions may be directed to Ronora Stryker, ASA, MAAA, SOA Research Actuary, at *rstryker@soa.org*.

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