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Session 4

Modeling Dynamic Policyholder Behavior Using Predictive Models

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SOA Predictive Analytics Seminar

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SOCIETY OF ACTUARIES

Agenda

- Background
- Traditional experience study vs predictive modeling approach
- Case Study 1: Lapse Modeling
- Case Study 2: Withdrawal Modeling
- Case Study 3: Customer Lifetime Value

Customers expectations of insurance are growing…

Easy to find… Google

Easy to buy… amazon

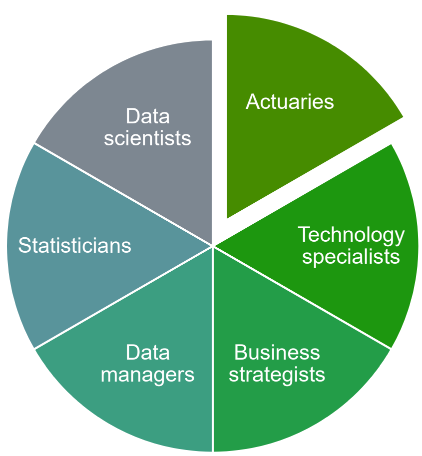
Easy to understand…

Personalized… NETFLIX

My team

I work with …

My role is …



Why study dynamic policyholder behavior

- **Motivation:** Dynamic policyholder assumption plays an important part in all aspects of a life insurer's liquidity and profitability yet there is very little guidance on this subject
- **Uncertainty:** There is enormous uncertainty around how policyholder behavior will emerge over the lifespan of business currently on the books of companies.
- **Impact:** The impact of policyholder behavior on the value and profitability of business is enormous, both for the industry as a whole and for individual companies. The impact could be in the billions of dollars for the companies with the largest exposure, and potentially long-term solvency. **Incremental improvements to understanding of customer behavior can have enormous dollar impacts.**
- **Availability of data:** For companies who have been consistently present in the VA marketplace, there is now over a decade of experience. In addition, there is valuable data on customers available from third party vendors. **While the experience data has some meaningful limitations in forecasting future experience, the industry could likely gain significant value by using the available data to develop better forecasting tools.**

Industry Recognition of the Problem

Moody's Investors Service

Unpredictable Policyholder Behavior Challenges US Life Insurers' Variable Annuity Business

MOODY'S INVESTORS SERVICE

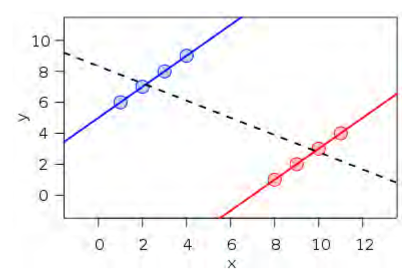
- "Though equity-market declines are generally seen as the biggest risk in VA contracts, most insurers effectively hedge that risk via derivatives. That leaves the less-easily hedged and more unpredictable policyholder behavior, and **particularly lapses, as a key driver of the profitability** of these popular products."
- "Companies selling VAs misestimated and underpriced lapse risk. Retention by policyholders of these guaranteed products was much greater than expected, causing insurers to take **significant, unexpected earnings charges and write-downs** over the past year and a half."
- "Recent experience for these guarantees provides [the takeaway that] … Companies tend to **retain customers that cost them the most and lose those that cost them the least**."

Source: Moody's Investor Service Global Credit Research - 24 Jun 2013

Traditional experience study vs predictive modeling approach

What does tabular analysis really tell us?

Actuaries have the lowest divorce rate at 17%!



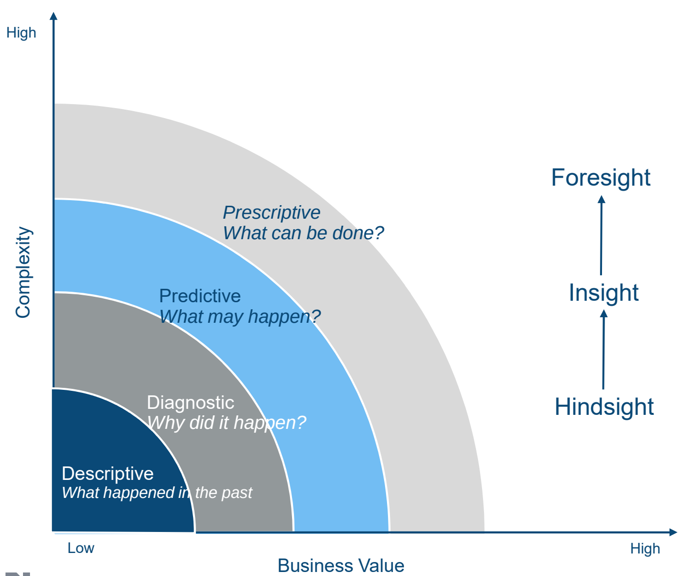
Descriptive analysis takes data and summarizes them using an average metric for the cohort but sometimes can be misleading if there are confounding variables

Source: FlowingData.com, Wikipedia

Traditional experience study vs predictive modeling approach

Traditional approach	Predictive model approach
▪ Traditional tabular analysis uses one way or two way splits of the data to analyze the impact due to a limited number of variables ▪ Aggregating data fails to control for confounding effects which may result in spurious correlation ▪ Assumptions are typically formulated to best fit most recent experience ▪ Validation is typically performed on the entire dataset rather than an holdout set ▪ Credibility measure is based on exposure rather than a probabilistic measure of the parameters ▪ Easy to use and implement but lack statistical rigor	▪ Captures a greater number of drivers without sacrificing credibility ▪ Uses all available data by effectively accounting for correlations in the model ▪ Interactions between variables can be fully explored without splitting the data ▪ Safeguards against overfitting by training models on a subset of data and validating the model on a holdout set ▪ ASOP 25: "In [GLMs], credibility can be estimated based on the statistical significance of parameter estimates, model performance on a holdout data set, or the consistency of either of these measures over time."

The four layers of analytics



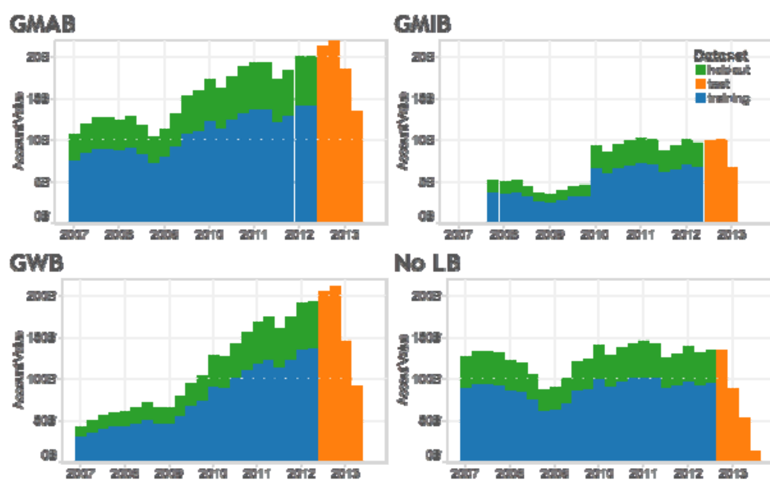
- Companies are evolving on the analytics spectrum from descriptive and diagnostic analysis to predictive and prescriptive analysis.
- Early adopters of this paradigm shift will gain a competitive advantage

Case Study 1: Lapse Modeling

Milliman VALUES Industry Lapse Study

A comprehensive and rigorous examination of industry VA lapse experience

- VA experience data
- 12 companies
- VAGLBs
- ~7 years of exposure
- 70% training set
- 30% holdout set



Milliman

Lapse Models: baseline and alternative implementations

- Baseline model

Lapse = Base Rate f(q) × ITM Factor f(ITM) → Tabular approach

- Baseline predictive model

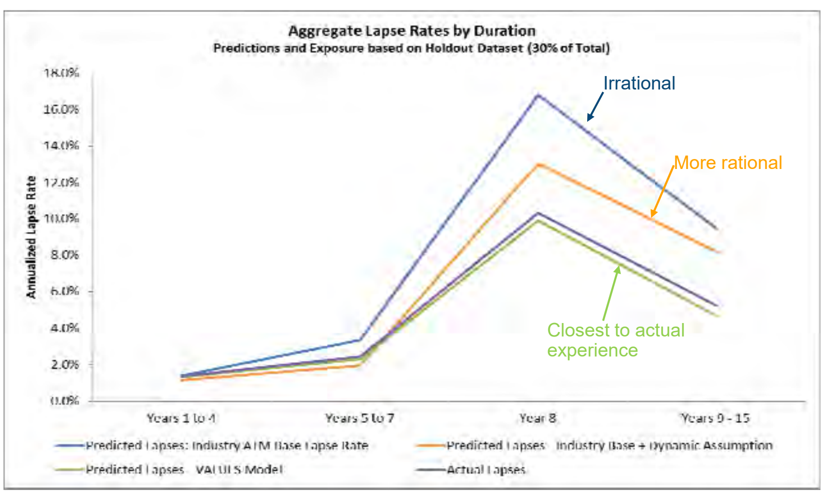
Log Odds = k_1 q + k_2 ITM Factor f(ITM)

- Milliman VALUES predictive model → GLM regression model

Log Odds = k'_1 q + k'_2 ITM Factor f(ITM) + • • •

Milliman VALUES Lapse Study

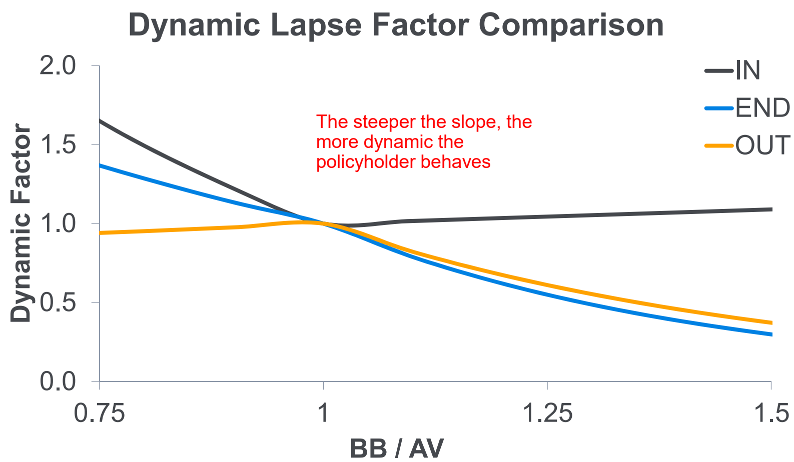
Post surrender charge lapse experience generally lower than current assumption



- Less guess work on the effect of base vs dynamic lapse
- Predictive model provides a single framework for analyzing and attributing the impact to both duration and moneyness jointly.

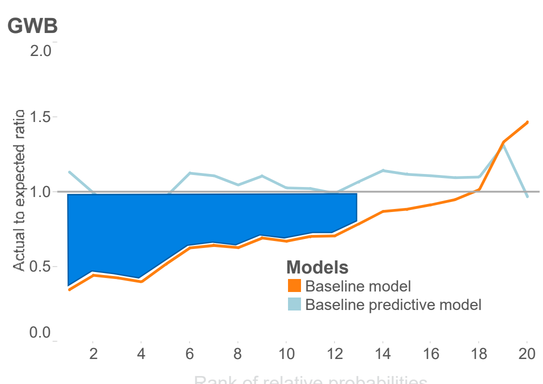
Milliman VALUES Lapse Study

Dynamic lapse function should vary depending on policy stage



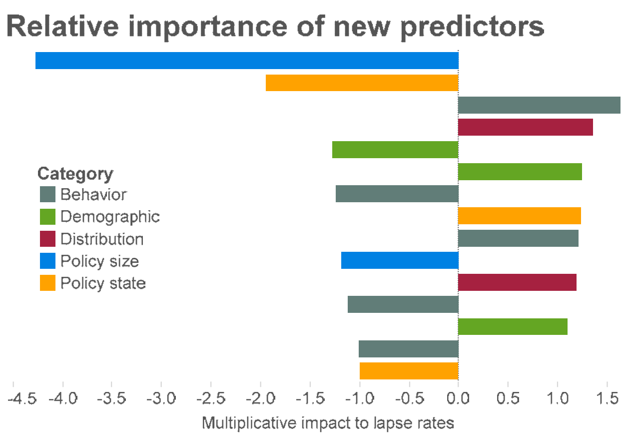
- Policyholders seem to be most efficient at the end of their surrender charge periods
- Interaction between variables can be fully explored

Predictive Model Improves Predictions



- Comparison of baseline model to baseline predictive model
- Policies sorted by ratio of predictions between the two models
- A/E plotted for groups each with 5% of records
- Left tails shows large area of over-prediction by baseline model (65+%)
- Moving to predictive model drops predictions to more reasonable levels

Algorithms can help accelerate variable selection

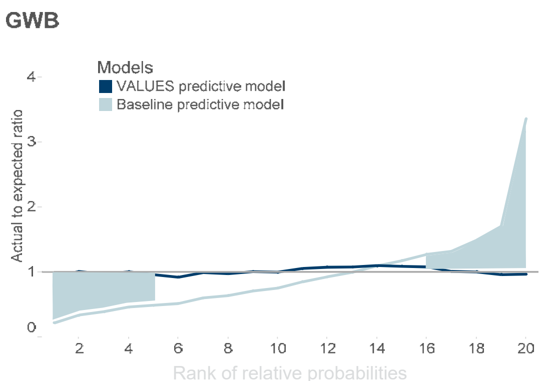


- When faced with hundreds of potential variables, computers algorithms are much faster at selecting important variables based on their influence on the behavior

Adding variables to the model without reducing credibility

- Policy state
  - − Recent issue indicators
  - + Policy anniversary
- Policy size variables
  - ▪ account value
  - – surrender charge ($)
- Behavior variables
  - – Time from policy issue to rider purchase
  - – Allocation to equities
  - + **Withdrawals above guarantee**
  - ▪ Recent withdrawal activity
- Demographic variables
  - – Attained age
  - + Gender is male
- Product design
  - – WB is richer than ROP
  - + Policyholder also has a GMAB
- Macroeconomics
  - ▪ Return relative to S&P
  - + **State unemployment information**
  - – CPI
  - – Change in treasury rate

Adding Variables Improves Predictions



- Comparison of full model to baseline predictive model
- Policies sorted by ratio of predictions between the two models
- A/E plotted for groups each with 5% of records
- Tails show areas of large over- and under-predictions by baseline predictive model: added variables bring predictions closer to experience

Case Study 2: Withdrawal Behavior

WB withdrawals: Motivating questions

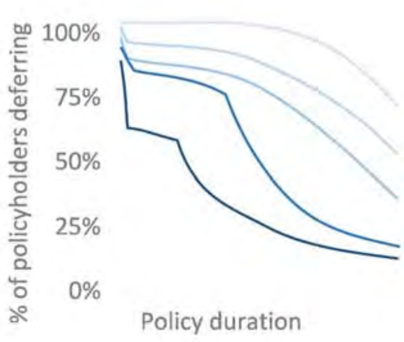
Election age	Lifetime withdrawal
55	4%
65	5%
75	6%
85	7%

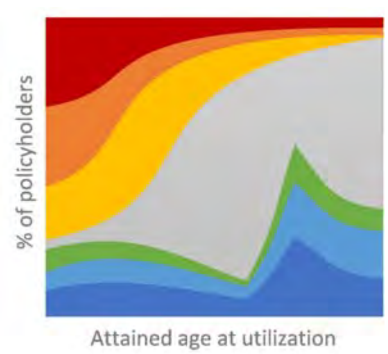
When does the first lifetime GLWB utilization occur?

How do the withdrawal amounts compare with the maximum guaranteed GLWB amounts?

Icons made by Freepik from www.flaticon.com

WB Withdrawals: Takeaways





- Policyholders who are older at issue tend to utilize their policies sooner
- Qualified policyholders will start their withdrawals sooner after age 70

- Less than half of all policyholders currently taking GLWB withdrawals utilize their GLWB benefit with 100% efficiency
- Utilization inefficiency is a driver of lapse

Case Study 3: Customer Lifetime Value

Thought Experiment

Is it possible that we would better be able to predict the behavior of individual policyholders if we knew about……

- **… their life events (death of spouse, marriage, divorce, events in lives of their children)**
- **… how their financial assets and investments are performing?**
- **… whether they are current on their mortgage or have paid it off?**
- **… whether they are in good health or have health problems?**
- **… if they have made big recent purchases?**

Much of this information may be readily available.

There might be other available data that serve as useful proxies for this information.

Annuity behavior modeling: progression of states

Current State

- Traditional one-way actuarial techniques to estimate expected lapse rates by age/duration and limited number of other characteristics using experience where it exists
- Primarily macro-oriented… little use of detailed information on policyholder characteristics
- Judgment and guesswork where experience does not exist

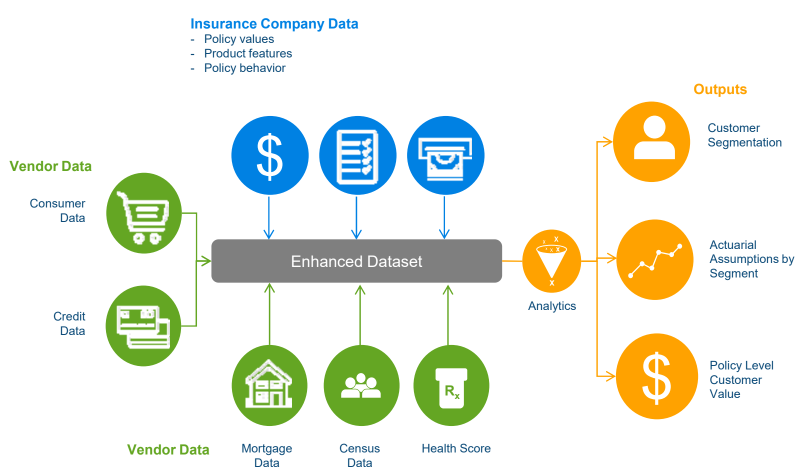
Next State

- Next-generation experience studies using policyholder longitudinal data.
- Use much wider set of explanatory variables readily available to company
  - Internal data (Product features, distribution channel, policyholder and contract characteristics)
  - Macro data (Economic data, financial market conditions)
- More sophisticated analysis techniques to find non-linear, multivariate effects, complex interactions

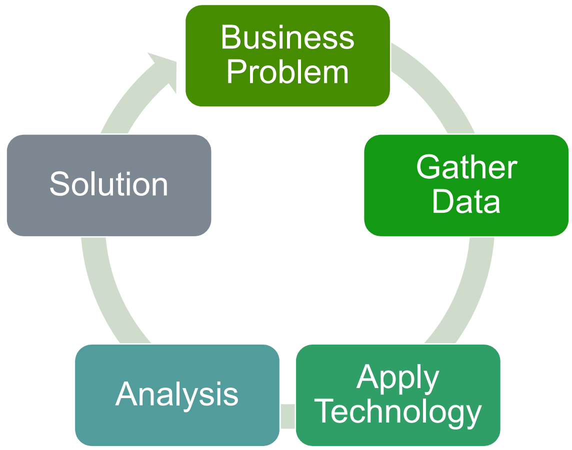
Advanced State

- Employ external consumer/financial/health and big/unstructured data sources in a full Predictive Analytics framework.
- Develop individual policyholder profiles
- Use insight to drive product development and create positive engagement with customers

What else can we learn about the customers?



The predictive model road map



Value of progressing to Predictive Analytics Framework

New Capabilities	Affected Business Functions
Improved Estimates of Future Lapse Rates	▪ **Hedging** better targeted to true liabilities, with improved tracking ▪ **Reserving** better aligned with actual liabilities, possible release ▪ **Capital Management** -- potentially more optimal use of capital
Identification of Policyholder "Value Profiles"	▪ **Product development** tailored to customer segments ▪ **Pricing new products** based on better information on customer behavior ▪ **Inducements and offers** to existing customers based on profiles
Real-time Data on Policyholder Activity	▪ **Continuous monitoring** of policyholders using up-to-date data and refreshed models ▪ **Identification of "at-risk" policyholders** for potential action
Reusable Framework for Other Customer Behavior Risks	▪ **Improved modeling and monitoring** of guarantee exercise/utilization ▪ **Improved modeling and monitoring** of inefficiency of withdrawals

Key Takeaways

Key Takeaways

- Reduced cost of storage and computing has largely lifted constraints around predictive modelling methods and applications
- Predictive models are well suited to investigating policyholder experience data
- Actuarial judgement is still required, in particular to avoid creating models that are hard to interpret or implement.
- A multidisciplinary team is necessary to successfully advance in this new area:
  - Subject matter expertise in the products, policyholder use of products, and the financial implications to insurers.
  - Data managers
  - Data scientists
  - Technology developers
  - IT infrastructure
- Building a predictive modelling framework requires investment of resources and technology but as competition in business increase, the benefits will outweigh the cost in the long run.

Thank You!

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