Equity-Based Insurance Guarantees Conference

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Predictive Analytics for Risk Management

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Predictive Analytics for Risk Management

Applications of predictive modeling for behavior risk

2017 Equity Based Insurance Guarantee Conference
November 7, 2017 1330 – 1430 hours

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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.**

Traditional experience study vs predictive modeling approach

Traditional 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
- 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

Predictive model approach

- 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.”

Lapse Models: baseline and alternative implementations

- Baseline model

Lapse = Base Rate f(q) × ITM Factor f(ITM)

- Baseline predictive model

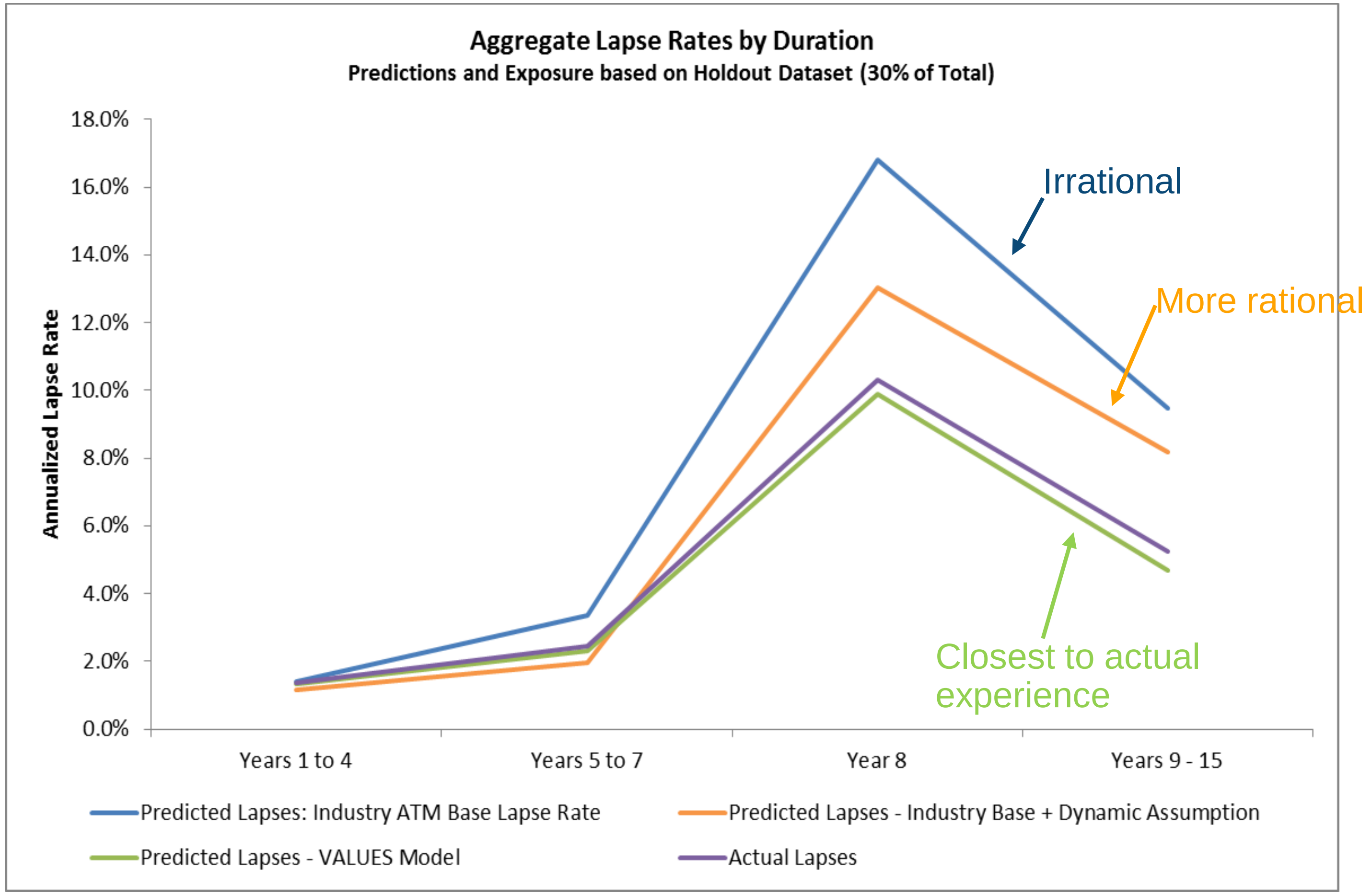
Log Odds = k_1 q + k_2 ITM Factor f(ITM)

- Milliman VALUES predictive model

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

Based on GLM regression model

Why do policies lapse?

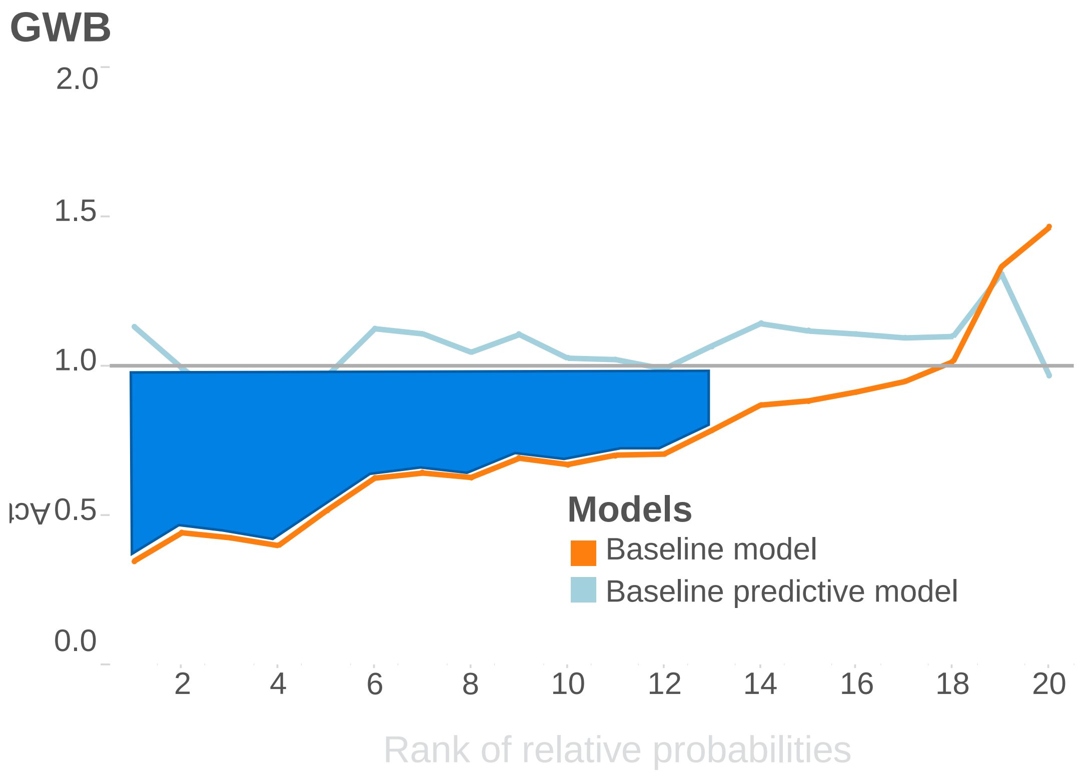


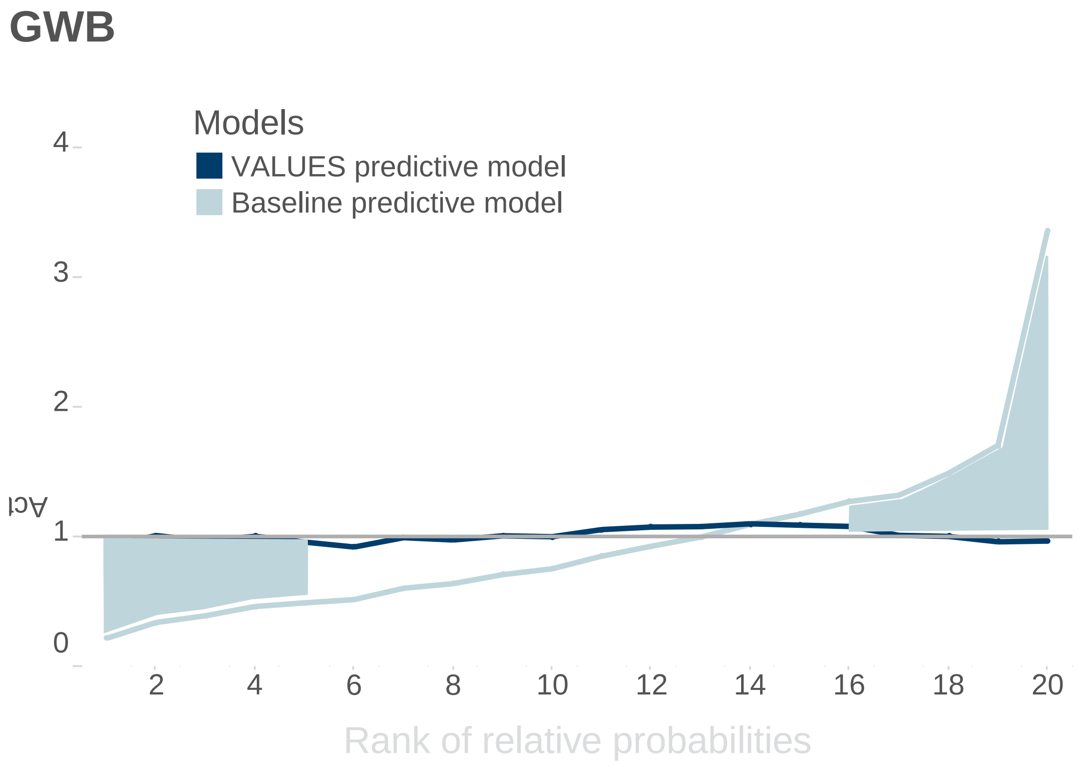
- Impact of duration vs moneyness vs surrender charge period?
- Predictive model provides a single framework for analyzing and attributing the impact
- Less guess work on the effect of base vs dynamic lapse
- More flexibility to reflect interacted variables

Algorithms can help accelerate variable selection

- 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

Predictive model improves predictions





- Comparison of baseline tabular model to baseline predictive model
- Comparison of full predictive model to baseline predictive model

WB withdrawals: Motivating questions

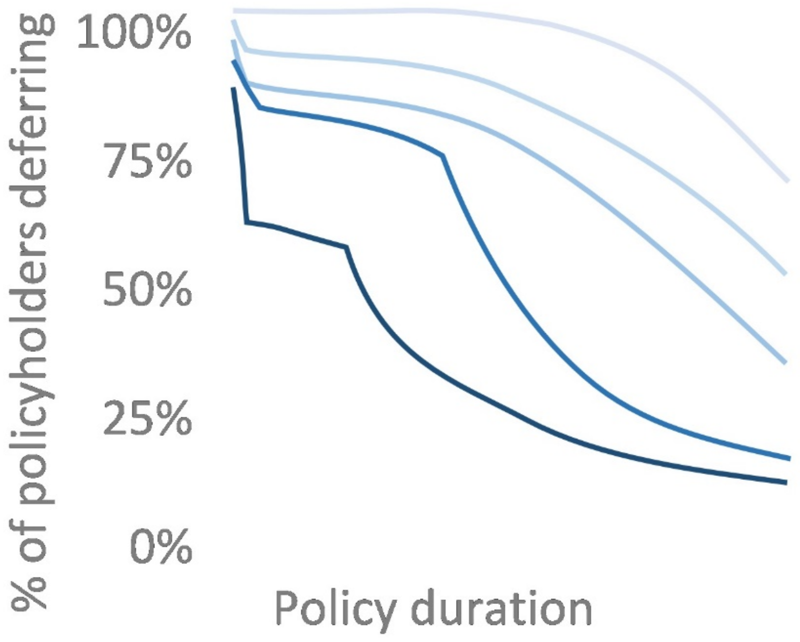
Election age	Lifetime withdrawal
55	4%
65	5%
75	6%
85	7%

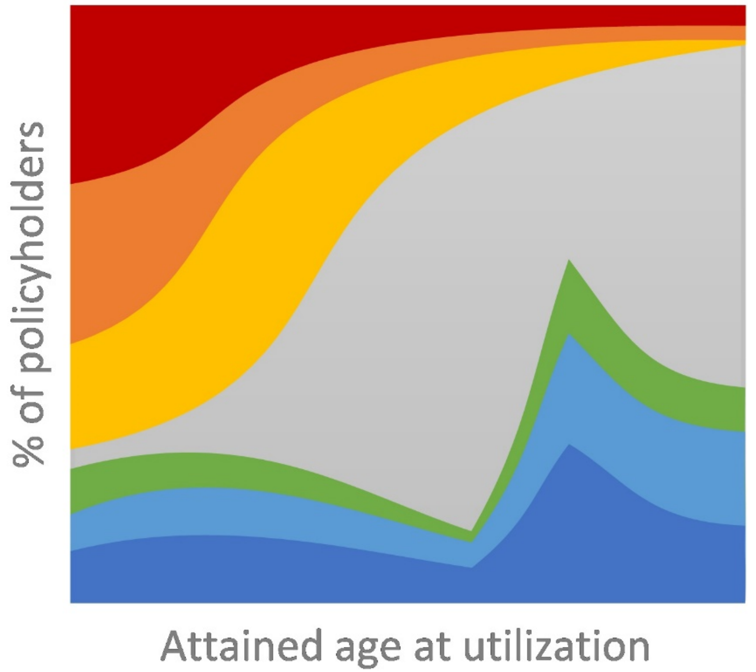
When does the first lifetime GLWB utilization occur?

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

Icons made by Freepik from www.flaticon.com

WB Withdrawals: Takeaways

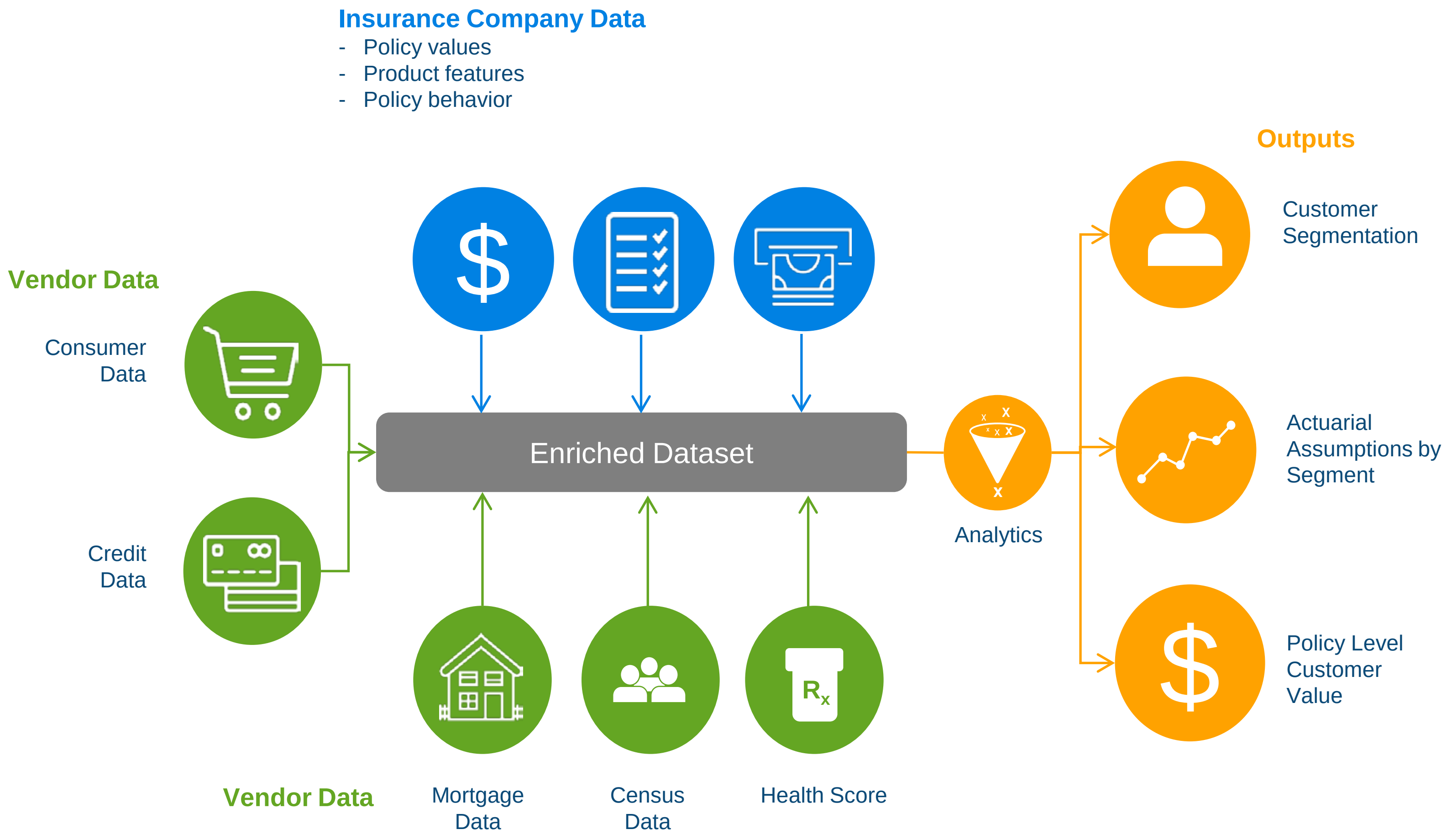




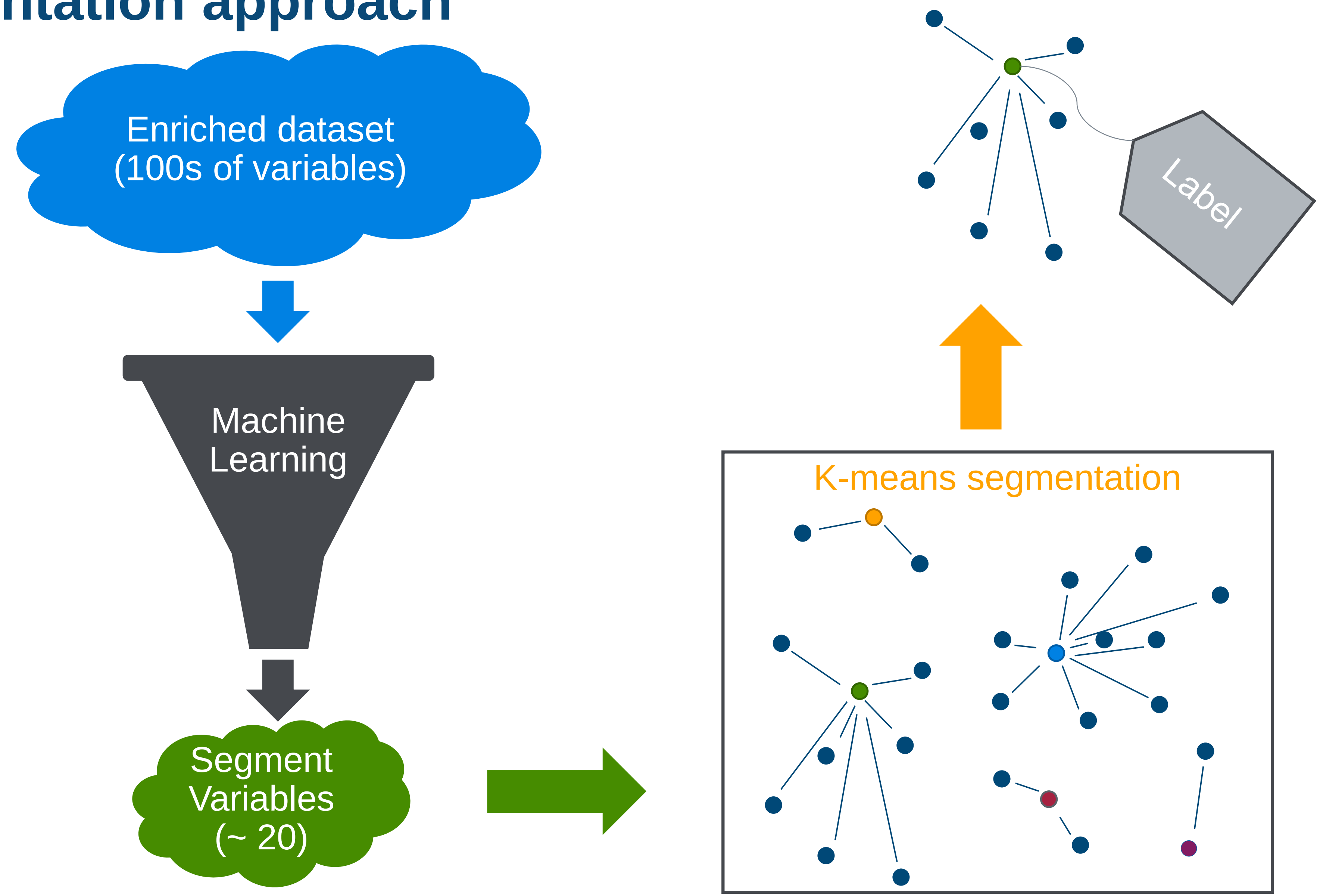
- Policyholders who are older at issue tend to utilize their policies sooner
- Qualified policyholders will start their withdrawals sooner after age 70

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

Building a data driven analytics framework



Segmentation approach



What type of customers are you selling to?

In **Debt**:
Low credit scores, high counts of credit delinquencies in the last five years

Lower Income:
Lower than average education levels, home values, and income levels

Middle Income:
Slightly higher than average education levels, home values, and income levels

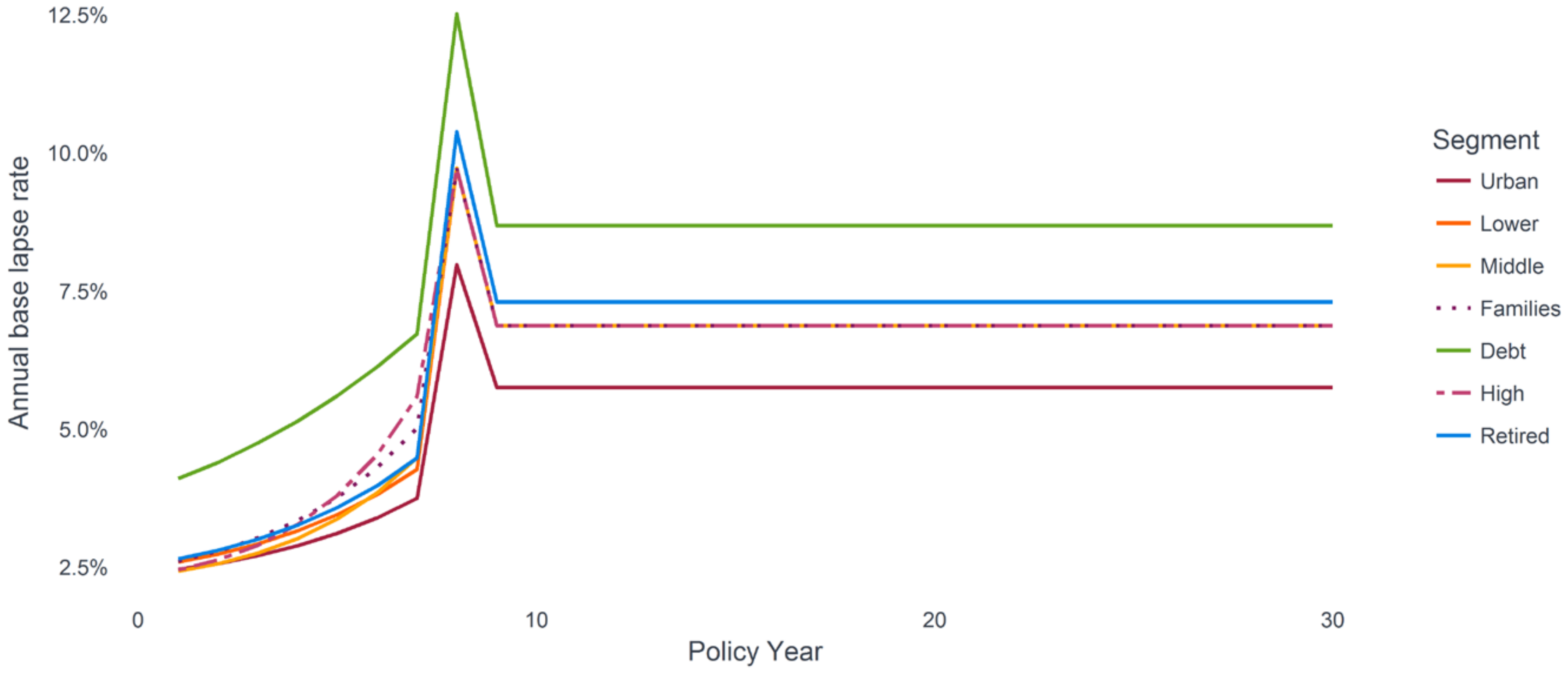
High Income:
Highest education levels, home values, and income levels

Urban Renters:
Live in high population density areas, with low proportion of homeowners

Families:
More likely to have children living at home, younger on average

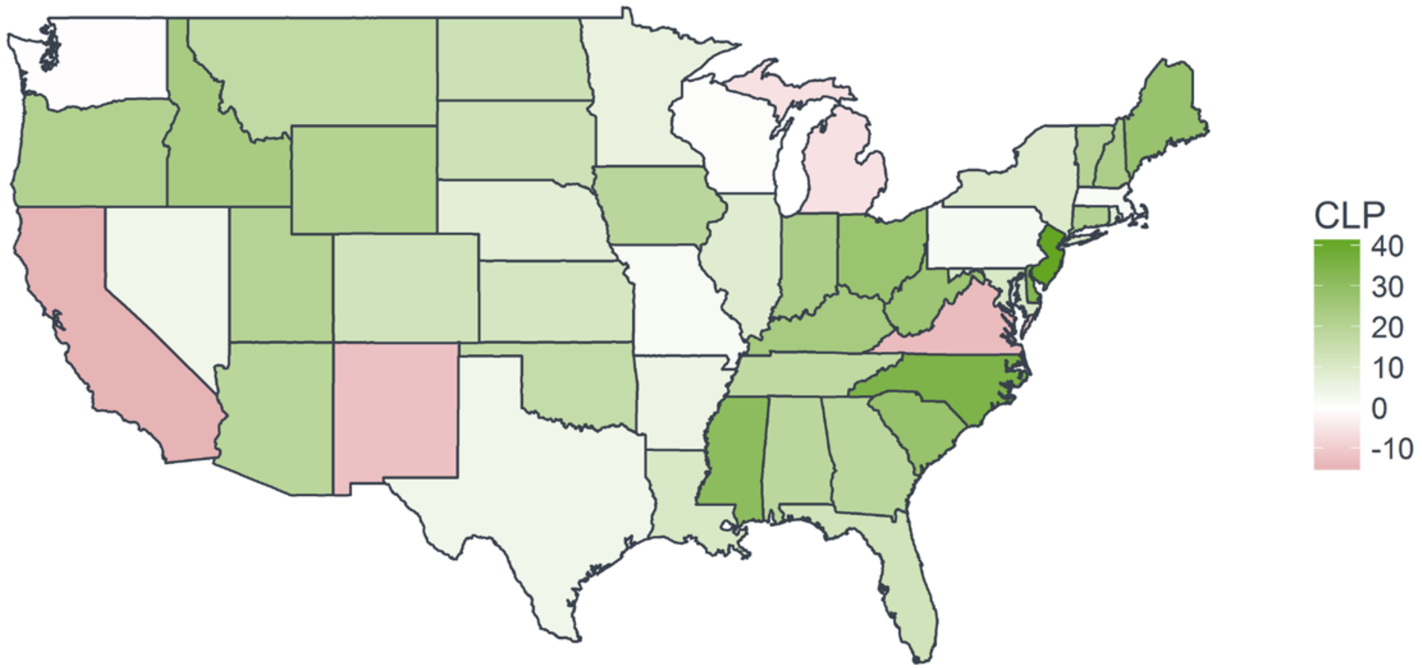
Retired:
Likely to be older, and live in areas with high proportions of individuals over the age of 65

Lapse rates by customer segments



The “In Debt” and “Retired” segments, shown above in green and blue respectively, have the highest base lapse rates during the shock lapse and post surrender charge period durations.

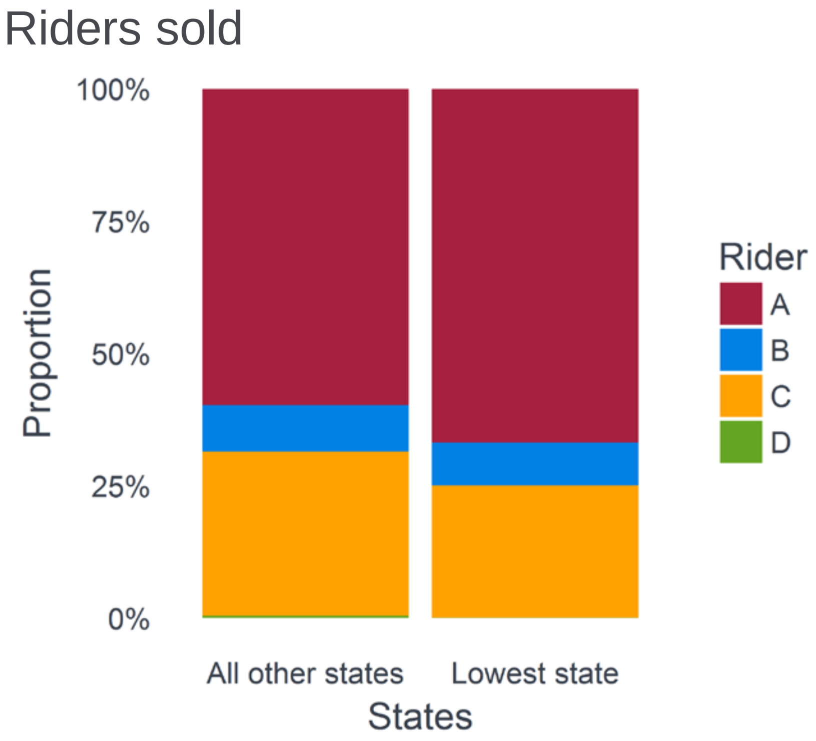
Geographical distribution

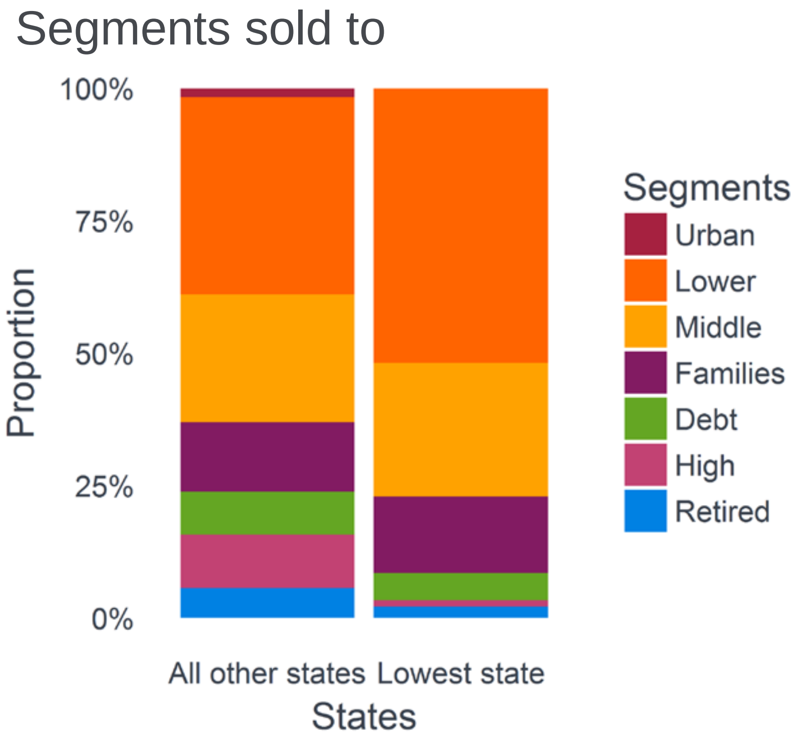


States in the darkest green are on average the most profitable in the block, while those in red are on average unprofitable.

Distribution strategy

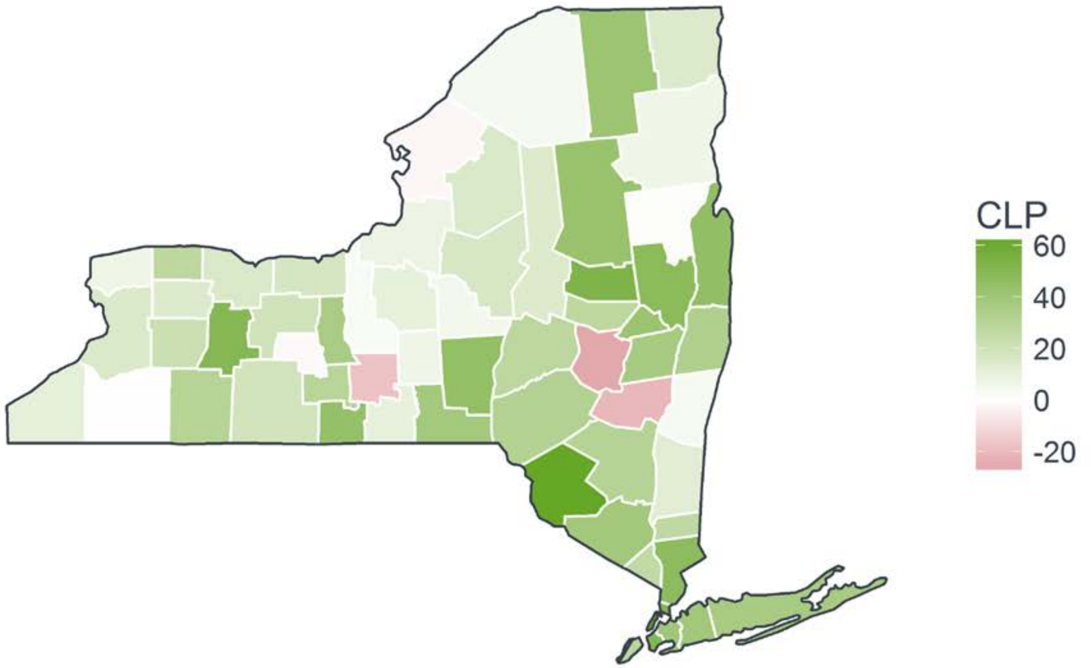
Why one state may be less profitable than the rest of the country





The map on the previous slide identifies the least profitable state, to answer why we dig into what they've sold and who they've sold it to. The distribution of products sold is very similar to the rest of the country but they've sold to a noticeably different mix of segments.

Geographic granularity



Depending on the concentration of data available we can drill down even further, this map demonstrates the average profitability of counties within the state of New York. This drill-down can be as granular as the available data.

What are the applications?

Can companies identify profitable business based on customer segments?

What are the main drivers of customer behavior? How valuable is external data?

Using data and models to identify anomalies

How can companies manage and improve the value of their inforce business?

Thinking about behavior assumptions as a distribution rather than a single estimate

Identifying top performing agents and linking to customer value

Key Takeaways

- Predictive models are well suited to applications in customer behavior and customer segmentation
- Data enrichment gives a more comprehensive understanding of customer profiles by linking company data with external data sources
- Actuarial judgement is still required, in particular to avoid creating models that are hard to interpret or implement.
- Insights from enriched dataset can be used to develop individual policyholder profiles, set behavior assumptions, drive product development and ultimately create positive engagement with customers.
- Building a predictive modelling framework requires investment of resources and technology but with increased demand for competitive differentiation, the benefits will outweigh the cost in the long run.

“You can’t manage what you don’t measure.”

Thank You!

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