Milliman VALUES™ 2019 GLWB industry lapse study

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In 2014, Milliman kicked off a series of variable annuity (VA) policyholder behavior experience studies using predictive analytics, starting with an industry lapse study. The goal of our Milliman VALUESTM series is to evaluate and improve common assumptions using advanced analytics, and to provide implementable suggestions.

Our 2019 Milliman VALUES Guaranteed Lifetime Withdrawal Benefit (GLWB) industry lapse and utilization studies included 3.1 million policyholders from eight large VA writers, representing roughly \$360 billion of initial account value and covering a range of GLWB product designs as well as demographic attributes. Our experience spanned from 2007 through the beginning of 2019. We studied when policyholders chose to begin taking lifetime withdrawals, how efficiently they continued to take them thereafter, and what drove them to lapse. With this lapse study, we significantly increased the amount of exposure in late durations, allowing us to better calibrate behavior out of the surrender charge period. We also investigated a broader range of lapse drivers.

2019 lapse study takeaways

These are some of the insights from our 2019 GLWB industry lapse study. Figures in this section are based on the industry data supporting the lapse study and are stylized to convey relative likelihoods of lapse for the sake of comparison. Individual company experience will differ based on the demographic composition and product features in its block.

During the surrender charge period, policyholders are sensitive to moneyness only when they are out-of-the-money. In this iteration of the lapse models, we included piecewise splits to calibrate distinct moneyness sensitivities along the range of moneyness values. When a policyholder is out-of-the-money—i.e., when the account value exceeds the GLWB benefit base—they show sensitivity as though they were out of the surrender charge period. However, when they are inthe-money, their sensitivity to moneyness is relatively flat.

Figure 1 shows our baseline model's dynamic lapse curve, segmented by surrender charge phase.

FIGURE 1: ANNUAL LAPSE PREDICTION FOR DIFFERENT UTILIZERS



During the surrender charge period, utilization behavior drives distinct moneyness sensitivities. Though policyholders in aggregate appear relatively insensitive to moneyness during the surrender charge period, withdrawing policyholders in the middle of the surrender charge period exhibit more typical behavior, in that they are less likely to lapse if their withdrawal benefits are in-themoney. Conversely, deferring policyholders show slightly inverted lapse sensitivities to moneyness. It is possible that withdrawing policyholder-advisor tandems are more aware of the value of the withdrawal benefit, while deferring tandems are more often reacting to poor market movements by lapsing.

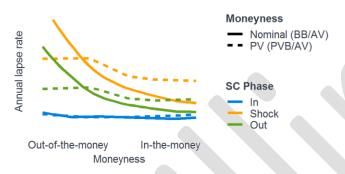
Nominal moneyness does a better job predicting lapse behavior than does the VM-21 present value definition of moneyness. The predictive model with nominal moneyness performed better on a holdout data set than a corresponding predictive model with VM-21's definition of present value moneyness, as measured by entropy error, or log loss. We further confirmed that the fit was better for the nominal moneyness model across these six data segments:

- In the surrender charge period, older and younger than attained age 70 (75th percentile of industry observations)
- At the end (shock) of the surrender charge period, older and younger than attained age 70
- After the shock period, older and younger than attained age 70

Figure 2 shows predicted annual lapse rates by moneyness for a set of 65-year-old synthetic policyholders. We see that policyholders are much more sensitive to *nominal* moneyness after the surrender charge period, and this shows in part why the nominal moneyness model produces more accurate predictions.

We suspect that attained age is a culprit for reduced sensitivity to the present value of moneyness. Younger policyholders have more expected future payments, which increases moneyness, but younger policyholders are also more likely to have liquidity needs and financial incentive to lapse. These competing age effects likely dilute policyholder sensitivity to this particular definition of present value moneyness.

FIGURE 2: ANNUAL LAPSE RATES, SEGMENTED BY SURRENDER CHARGE PHASE AND MODEL, ACROSS MONEYNES



Lapse trends toward an ultimate rate of 2.0% in the industry.

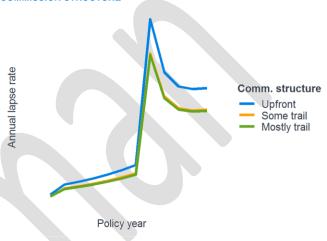
For durations that are more than five years out of the surrender charge period, and for moneyness ratios (BB/AV) greater than 2.0, lapse rates become insensitive to further increases in these variables. This implies that lapse rates may stabilize over time for efficiently withdrawing policyholders. Using our predictive model to control for late durations, deep in-the-moneyness, and efficient withdrawal behavior, we estimated that such policyholders have an "ultimate" lapse rate of about 2.0%.

This agrees with our data segmentation result from last year, which suggested about the same ultimate lapse rate for the industry. That exercise also revealed that individual companies in our study vary from about 1% to 2.5% in their ultimate lapse rates.

Policyholders whose advisors were compensated with a 100% up-front commission show a greater likelihood to lapse. Figure 3 shows annual lapse rates by policy year, segmented by commission structure. We categorize commission structure into three groups: all up-front, some trail commissions, and mostly trail commissions. Those policyholders with policies sold on an up-front commission basis show noticeably greater

lapse rates across all durations. Such a policyholder is about 1.25 times as likely to lapse as an otherwise similar policyholder whose advisor was compensated with at least some trail commissions. There is little difference between our trail commission categories. These effects are averaged across distribution channels.

FIGURE 3: ANNUAL LAPSE RATES BY DURATION, SEGMENTED BY COMMISSION STRUCTURE



OTHER FINDINGS

- Though relatively flat across the entire surrender charge period in aggregate, moneyness sensitivity increases between the first and last years of the surrender charge period.
- Policies sold through a banking channel are more likely to lapse than those sold through other channels.
- Older policyholders with single-life GLWB contracts are generally less likely to lapse than younger policyholders.
- Males with single-life GLWB contracts are more likely to lapse than both females with single-life GLWB contracts and joint contract policyholders.
- Non-lifetime withdrawals indicate future lapses, and the effect lasts at least one year.
- Policyholders with smaller policies—i.e., lower initial premiums—lapse more often.

Future plans

Building off our VALUES studies, we are currently researching a number of distinct items, including:

- Investigate third-party data as drivers of policyholder behavior.
 We expand on this in the following section.
- Compare our industry variable annuity experience and policyholder behavior models to the assumptions prescribed in VM-21.
- Investigate the effects of macroeconomic factors on variable annuity lapse behavior (beyond dynamic moneyness factors).
- Conduct an industry study on indexed annuities.

Our goals

This study builds on the effort we began in 2014 to provide insights into policyholder behavior based on scientifically sound principles. The report contains a comprehensive analysis of all the drivers we studied related to GLWB lapse behavior, and for each driver the report provides more details, including charts, tables, etc. It also provides both a baseline predictive lapse model function, with typical industry drivers, as well as details about our expanded lapse model. In this iteration of the study, our expanded model includes past utilization behavior, as well as age, gender, distribution channel, commission structure, and policy size as drivers of lapse. The baseline lapse model is designed for straightforward implementation in an actuarial projection.

We go beyond the report, however, giving subscribers access to Recon® GLWB, an interactive, web-based platform that allows them to visualize and download both the data and predictions from both models in an effective way. Subscribers also have access to the coefficients and model form of our linear predictive models. Recon GLWB is updated each quarter as participants send in updated experience data. Each year, we fully refresh the platform with updated models and new insights based on the VALUES studies.

Our goal is to continue to expand the insights we provide via the VALUES studies on the Recon platform to help our clients.

In that vein, we plan to use third-party data to better segment policyholders, providing a clearer picture of what drives policyholder behavior. Recon subscribers will be able to see data snapshots across these refined policyholder segmentation groups, and subscribers will also have access to predictive models driven by the third-party data policyholder segments.

More generally, we help subscribers by:

- Closely monitoring the emerging industry experience
- Using industry data to benchmark company experience against the industry and supplement assumption setting, particularly where a company's own experience is scarce
- Allowing companies with no GLWB products to get a view on policyholder behavior as they contemplate market entry
- Support in-force management and product development strategies



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For more information on the purchase of the full 2019 GLWB utilization or lapse reports, including access to Recon® GLWB, and to participate in our ongoing industry experience studies, please contact:

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