Understanding and modeling interest rate sensitivity on fixed index annuity

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Introduction

In the past decade, dynamic lapse assumptions for annuity products have not been a significant topic of discussion in the industry, mainly because the prolonged low interest rate environment has dampened dynamic behavior. Obvious challenges, such as the lack of industry consensus, limited credible company experience, and the absence of an established study framework, also complicate the review and update process. However, as market conditions, product designs, and regulatory environments evolve, the importance of revisiting and refining these dynamic assumptions continues to grow, making it essential for insurers to begin proactive reviews.

The first major external factor has been the shift in the economic market conditions. Before 2023, the rates offered on most new annuity products were not sufficiently attractive to induce a meaningful number of replacements, particularly for contracts issued during earlier, higher-rate eras. As interest rates began to rise in March 2022, new products offering more competitive crediting rates entered the market. Many insurers have observed lapse rates at levels not previously experienced.

On the regulatory front, the emergence of principal-based reserving (PBR) frameworks, such as VM-22 and the Bermuda Economic Balance Sheet (EBS), requires insurers to use their own best estimate assumptions in reserving, including dynamic behavior on deferred annuity products, further underscoring the need for insurers to revisit and strengthen their dynamic assumptions.

At the same time, the demand for a more sophisticated asset-liability management (ALM) program has increased, driven by both the desire to align assets with liabilities under PBR and insurers' efforts to enhance return on general account assets. To date, most of the sophistication has occurred on the asset side. Without appropriate dynamic lapse behavior captured on the liability side, the objectives of the ALM programs remain inaccurate and incomplete.

The task of reviewing and developing the interest rate component of dynamic lapse assumptions, however, has long been challenging. This difficulty arises from several sources. First, most policyholder experience data span a period characterized by persistently low interest rates, during which dynamic policy behavior was largely unobservable. Second, the competitive landscape is shifting, with innovative product designs offering policyholders more attractive index rates or higher upfront bonuses, which are not often captured in companies' assumptions. Finally, lapse behavior is strongly influenced by company-specific decisions on in-force management, which vary across firms and over time.

In addition to these factors, insurers take widely varying approaches to structure their dynamic lapse assumption, differing in functional form, parameterization method, and choice of predictive variables. As a result, the assumed dynamic behaviors vary significantly across companies, and there remains little industry consensus on the matter.

This paper aims to analyze and model interest rate sensitivity in fixed index annuity lapses, providing a framework for insurers to refine assumptions.

ECONOMIC DRIVERS OF SURRENDER

Before developing a mathematical framework for policyholder behavior, we must first identify the economic drivers of their decisions. This section examines the factors commonly incorporated into models, as well as other factors that can provide further explanatory value.

From the policyholder's perspective, the lapse decision is a choice between the economic value of the current policy $V(i)$ and the value from replacement $V(i')$ available on the market. The commonly recognized and modeled factors include the interest rate, the number of years of investment, and any additional penalties or bonuses associated with the replacement. This is expressed in a formulaic term as:

$$V(i) = Face\ amount\ \times i\ \times n$$

$$V(i') = Face\ amount\ \times (i'\ \times n - SC\% + Bonus\%)$$

where

i = rate of return on existing contracts, in percentage

i' = offered crediting rate on the replacement product, in percentage

n = expected years of future investment horizon

SC% = penalty for early surrender in the current contract, including recapture of existing bonus or any market value adjustments, in percentage

Bonus% = premium bonus offered by the replacement product, in percentage

The expression includes several simplifications to keep the formula concise. Besides assuming simple interest accrual, the same amount of credited interest is equally valued as a bonus or a surrender charge. This assumption is only approximately true because the bonus and surrender penalty at present should be valued higher than future interest, given the time value of money and the uncertainty surrounding future guarantees.

When $V(i')$ is greater than $V(i)$, and in the absence of external factors, a perfectly rational and efficient person should immediately lapse the policy; however, in reality, policyholder behavior is more nuanced than the perfectly rational behavior predicted by this model. What are some reasons for more complicated behaviors that are not captured in the simple model above?

- **Information asymmetry:** Insurance product rates are often far less transparent than traditional investments. To learn about current offers from various companies, policyholders typically must consult multiple insurance agents, which can make comparisons difficult. For index products, comparing rates across strategies and indices adds further complexity.
- **Individual circumstances:** Policyholders often avoid starting a new surrender charge period if it does not align with their investment horizon. This is especially true for older policyholders, who are less willing to be locked into long surrender periods even if a new policy appears more attractive. Behavioral factors also play a role. For example, risk aversion can discourage contract termination, as the lower rate of contract terminations observed during the COVID-19 pandemic period demonstrates. Decisions can also be delayed if policyholders are willing to wait for better options in the future.
- **Transaction costs and future lapse opportunities:** There are costs associated with monitoring and evaluating competing products and with the actual lapse process. A policyholder is unlikely to lapse to capture a few basis points of increased value. Moreover, if rates are expected to continue rising, it is preferable to wait for the optimal offer rather than repeatedly lapsing contracts to reduce transaction costs.
- **Value of the guarantee:** Policyholders may also consider the current benefits offered in their contracts rather than focusing solely on the crediting rate. For example, an individual who owns a policy with an existing ultimate crediting rate guaranteed at 4.5% may not want to lose that rate for a policy that offers a higher crediting rate guaranteed for 5 years (e.g., at 5.5%) but has an ultimate guaranteed crediting rate of 1%.
- **Agent behavior:** Despite Treasury rates peaking around Q3 2023, many insurers did not observe the peak in elevated surrenders until Q1 2024. Even then, experiences varied widely: Some companies saw only mild increases, while others faced sharp spikes in lapses. This inconsistency suggests that agents may exert substantial influence on lapse behavior. Agents are more likely to approach the policyholder when the new contract is significantly better than the existing one. Larger contracts tend to receive more agent attention and thus exhibit more efficient outcomes. Independent agents, who can offer products from multiple insurers, often drive higher lapse rates compared to career agents restricted to a single company’s offerings.

REPRESENTATION IN A DYNAMIC FORMULA

A dynamic function $f(x)$, showing the additive lapse rate due to rate movement based on the factors identified in the previous section, can be written as:

$$f((i' - i)n + Bonus\% - SC\%)$$

After some rearrangement of the terms, all the rates are in percentages:

$$f(i' + \left(\frac{Bonus\%}{n}\right) - i - \frac{SC\%}{n})$$

where

i = current crediting rate for a fixed account; for index accounts, companies often use the option budget, the current portfolio earn rate, or a proxy portfolio rate

i' = competitor rate assuming a constant competitor spread over Treasury based on the company's internal view of competitors

n = assumed years of investment horizon

bonus% = company's view on the bonus rate that the competitor can offer

Historically, most companies did not consider bonuses when assessing the rates competitors could offer. Still, in recent years, a growing number of annuity contracts have started to provide rich bonus benefits. Some can exceed 20%. A significant lapse has resulted because the bonus is more than sufficient to offset the surrender charge and the uncertainty surrounding future crediting rates. To account for this, one can also include the annualized bonus rate in the competitor rate (*i'*) by increasing the assumed competitor spread. To simplify the formula, the function can be written as:

$$f((i' - i - \frac{SC\%}{n})$$

The next question is: What is the form of the formula? Is it convex, concave, linear, or more complex? The formula below is a common form that includes two additional parameters: a scale parameter *Z*, which controls the magnitude of the change, and an exponent *k*, which controls the shape of the function.

$$f(x) = Z * \left(i' - i - \frac{SC\%}{n}\right)^k$$

A linear formula, when *k* = 1, suggests that the policyholder's behavior is consistent as long as the same level of interest movement has been observed. A concave formula, such as some arctangent formulas or the above formula when *k* < 1, suggests that policyholders are sensitive to small rate movements but become less sensitive as the value differential increases. Finally, the formula is convex for *k* > 1, indicating that policyholders are insensitive to small rate movements but become more responsive as the rate movement increases.

The chart below illustrates the assumed dynamic lapse effect for a single parameterization across various shapes of the dynamic lapse function.

FIGURE 1: ASSUMED DYNAMIC LAPSE EFFECT FOR A SINGLE PARAMETERIZATION ACROSS VARIOUS SHAPES OF THE DYNAMIC LAPSE FUNCTION

DIFF = *i' – i*	CONVEX 2 * (DIFF*100)^2	CONCAVE ARCTAN(DIFF * 0.1)/(Π/2)	LINEAR (DIFF*100) * 4
0.00%	0.00%	0.00%	0.00%
0.50%	0.50%	3.18%	2.00%
1.00%	2.00%	6.35%	4.00%
1.50%	4.50%	9.48%	6.00%
2.00%	8.00%	12.57%	8.00%
2.50%	12.50%	15.60%	10.00%

DIFF = $i' - i$	CONVEX 2 * (DIFF*100)^2	CONCAVE ARCTAN(DIFF * 0.1)/(Π/2)	LINEAR (DIFF*100) * 4
3.00%	18.00%	18.55%	12.00%
3.50%	24.50%	21.43%	14.00%
4.00%	32.00%	24.22%	16.00%
4.50%	40.50%	26.92%	18.00%
5.00%	50.00%	29.52%	20.00%

If sufficient experience were available, insurers could proceed to select the shape, determine relevant predictive variables, and parameterize the lapse model. However, credible data across the full range of interest rate differentials have generally been unavailable because most annuity products' experience has occurred during periods of declining interest rates.

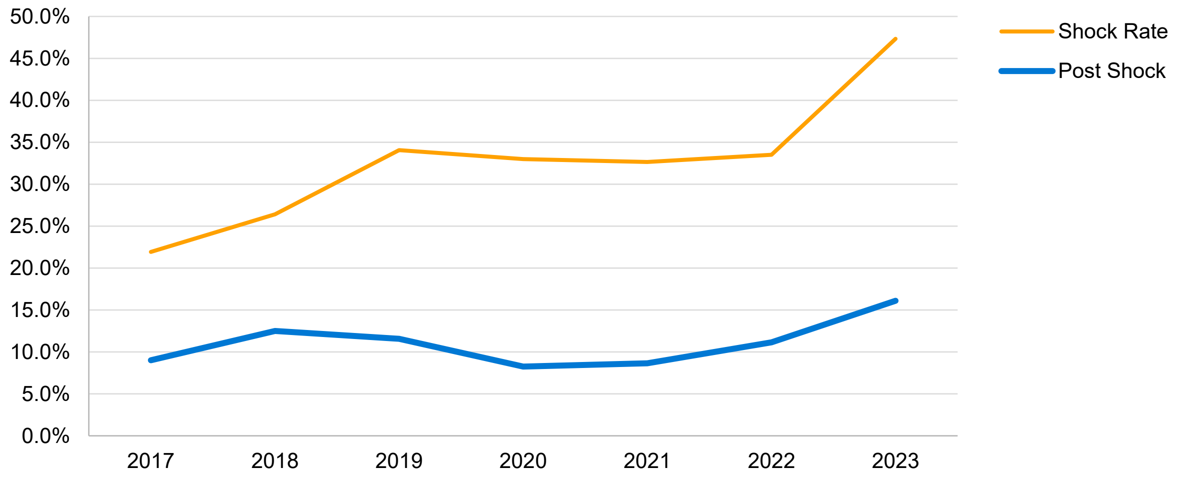
Moreover, external factors, such as the COVID-19 pandemic or macroeconomic disruptions in the job market, introduce confounding effects on lapse behavior, further complicating the isolation of pure interest rate sensitivity. As such, reliance on raw experience data without adjustment may lead to biased parameter estimates. It is therefore critical that actuaries exercise expert judgment and apply prudent methods when setting the assumptions rather than depending exclusively on observed data.

A study with industry experience

The analysis in this paper starts with the dataset collected during Milliman's annual industry experience studies on fixed index annuities (FIA). For this paper, we selected a subset of the dataset on shock-year and post-shock-year accumulation FIA policies from several large carriers with robust option budget information, covering issues from 2000 to 2021, and study dates from 2017 to 2023. The purpose of the study is to illustrate an approach that companies can leverage to review and calibrate their dynamic lapse assumptions when they have a credible amount of experience and to share results that could be used for benchmarking.

The Figure below summarizes the aggregate annual lapse rate observed in the study.

FIGURE 2: ANNUAL LAPSE RATE, 2017 TO 2023



We took a predictive analytics approach to model the effects of several non-interest rate factors and then evaluated the impact of interest rate changes on lapse rates. We will first define a base lapse rate that accounts for policy size and age, and then introduce a dynamic lapse adjustment.

$$Total\ lapse\ rate = base\ lapse * attained\ age\ mutiplier * size\ mutiplier + dynamic\ lapse\ adjustment$$

CALIBRATION OF PARAMETERS

One of the key challenges in calibrating a dynamic formula is the inability to isolate and individually calibrate each parameter against experience. Additionally, there is often no clear metric to determine which variables meaningfully capture the dynamic behavior. As a result, actuarial judgment plays a significant role throughout the process. In the following section, we present an alternative approach to developing and calibrating the dynamic model using predictive modeling.

Each model was built iteratively by adding a new factor at each step, reestimating the entire model (excluding the base lapse) using maximum likelihood, and deciding whether the new factor had sufficient explanatory power to remain in the model using the Bayesian Information Criterion (BIC) and judgment. For this study, the quarterly exposure was 872,234, so the BIC decision rule is to accept a new factor if it adds at least

$$0.5 * ln(872{,}234) \ = 6.84$$

to the log-likelihood for each additional parameter.

In the next section, we present results as *(additional log-likelihood, additional parameters)* relative to the previous step. With only the base lapse assumption in the prior step, the log-likelihood is -146,285.

DEFINITION OF BASE LAPSE

For the study, we define the base lapse rate as the average actual base lapse rate for policies with a current option budget (*i*) that is within 50 bps of the market rate (*i'*), defined as the 7 Year Treasury less 25 bps, varying by the studied company and surrender charge status. In practice, companies often have different definitions of base rate and competitor rate reflecting their own view of the product and market competitiveness.

The average annual base shock lapse rate is approximately 33%, whereas the average base post-shock lapse rate is approximately 11% for the subset of experience we selected. Detailed base lapse data in the study varies by company and therefore will not be disclosed.

To further adjust the base lapse rate, we found that attained age and account value have meaningful effects on lapse rates. For policies in the shock-year or post-surrender charge period, the lapse rate is positively correlated with policy size. Most of the FIA policies in our dataset have face amount less than $200,000, and lapse rates increase with face amount.

Then we layer on a multiplier based on attained age. Lapse rates are higher during the early-to-late retirement ages (50 to 79) than at younger or older ages for policies of the same duration.

FIGURE 3: SIZE MULTIPLIER

SIZE MULTIPLIER	
Less than 100k	0.98
100k to 200k	1.23
200k to 300k	1.35
300k to 400k	1.39
Greater than 400k	1.52

FIGURE 4: AGE MULTIPLIER

AGE MULTIPLIER	
0-49	0.89
50-59	1.05
60-69	1.19
70-79	1.07
80+	0.69

Both additions turn out to be statistically significant based on the definition in the previous section, as summarized in figure 5 below.

FIGURE 5: IMPACT TO LOG-LIKELIHOOD FROM ADDING SIZE AND AGE FACTOR

STEP	DESCRIPTION	INCREASE IN FREE PARAMETERS FROM PRIOR STEP	INCREASE IN LOG-LIKELIHOOD FROM PRIOR STEP
0	Base lapse only	8	
1	+ Size factor	5	367
2	+ Attained age factor	5	903

Figure 6 below summarizes the actual-to-expected (A/E) rate by study year, where the expected is based on the base lapse rate with policy size and age adjustments.

FIGURE 6: ACTUAL-TO-EXPECTED RATE BY STUDY YEAR WITH BASE LAPSE ONLY

STUDY YEAR	ACTUAL LAPSES COUNT	EXPECTED LAPSE COUNT	A/E
2017	1,950	2,230	87%
2018	2,144	2,368	91%
2019	4,898	4,592	107%
2020	7,486	7,619	98%
2021	7,638	8,629	89%
2022	7,884	8,183	96%
2023	5,841	4,069	144%
Grand total	37,841	37,690	100%

How are interest rates adjustment brought into the model?

We started with as basic a model as possible—no factors for interest rate items. Then, incorporating an interest-sensitivity component into one form of the dynamic lapse function as discussed in the earlier section, where shape parameter *k* has the flexibility to define the function as linear, convex, or concave, as below:

$$Dynamic\ Lapse\ Function = Z * \left(i' - i - \frac{SC\%}{n}\right)^{k}$$

Where *i'* is defined as the 7 Year Treasury rate minus 25 bps, *i* is the current option budget. Because the study only includes out-of-surrender charge policies, the term $\frac{SC\%}{n}$ is zero.

Reviewing the year-by-year A/E experience summarized above, lapse rates begin to rise in 2023, even though the Fed started raising rates in Q2 2022. The impact in 2022 is far less apparent, posing challenges if the model were calibrated using 2022 experience. This could be due to several reasons, including:

- COVID-19 pandemic impact reduces overall lapses, as well as interest rate sensitivity
- Delay for policyholders and agents in taking actions for rate movement

To account for the effect of the delay, some companies include a lag in the market rate. In the study, we introduced a six-month lag to the previously defined market rate.

There is also significant variation in A/E when examining the 2023 study results by company. The A/E in 2023 ranges from 103% to 190% across companies, despite the base lapse rate already being company-specific, owing to differences in product design, distribution channels, and renewal strategies. Therefore, having a single set of parameters calibrated to aggregate the experience of all companies would significantly understate the interest rate sensitivity of some companies and significantly overstate the sensitivity of others.

For that reason, we took the approach to calibrate the dynamic lapse function by company. The figure below summarizes that, under each set of fixed shape parameter *k*, the scale parameter *Z* is calibrated based on maximum likelihood estimation and the increase of likelihood from the prior step without dynamic adjustment. The study will focus on the scenario in which *i'* > *i* because our primary objective is to examine the increase in lapses as interest rates rise.

FIGURE 7: IMPACT TO LOG-LIKELIHOOD FROM ADDING DYNAMIC LAPSE ADJUSTMENT

K WHEN i' >= i	Z WHEN i' >= i	LIKELIHOOD INCREASE FROM STEP 2
2	0.2 to 3.0	871
1.5	0.4 to 4.5	875
1	0.6 to 6.5	837
0.5	0.9 to 8.5	750

Incorporating an interest-sensitivity component into the lapse function adds (depending on the exact specification) around 800 to the log-likelihood, which clearly reflects interest rate changes that are in some way a significant improvement. While the increase in likelihood attributable to different function shapes is similar, the calibrated *Z* parameters would vary significantly across companies.

The improvement is also evident in the year-by-year change in A/E. In particular, the aggregated A/E in 2023 increased from 144% to 106% after incorporating a dynamic adjustment in one of the examples above, with *k* = 1.5.

FIGURE 8: ACTUAL-TO-EXPECTED RATE BY INCLUDING DYNAMIC LAPSE ADJUSTMENT

STUDY YEAR	ACTUAL LAPSES COUNT	EXPECTED LAPSE COUNT	A/E
2017	1,950	2,082	94%
2018	2,144	2,219	97%
2019	4,898	4,221	116%
2020	7,486	7,042	106%
2021	7,638	8,192	93%
2022	7,884	8,900	89%
2023	5,841	5,518	106%
Grand total	37,841	38,175	99%

Conclusion

While industry studies such as this one provide valuable benchmarks and insights into general lapse behavior for FIAs, companies must incorporate their own experience and judgment when setting dynamic lapse assumptions. Company-specific factors—including product features, surrender charge structures, distribution methods, marketing strategies, and underlying policyholder demographics—can materially impact lapse rates and their responsiveness to changes in credited rates, market conditions, and policyholder options. Relying solely on industry data risks overlooking these unique characteristics, potentially leading to assumptions that misrepresent a company's actual risk profile. Internal experience enables more accurate, tailored modeling, especially for blocks with sufficient credible data. However, industry studies serve as an essential resource for benchmarking, including when internal data are limited or lack credibility or when launching new products for which historical experience does not yet exist. In such cases, industry benchmarks can guide initial assumptions, with a transition to company-specific experience as credible data emerges over time.

Additionally, while a dynamic behavior model can help capture broad trends in individual policyholder behavior, it becomes less effective when behaviors are driven by agents, whose actions often occur in waves and follow unpredictable patterns. Companies need to distinguish agent-driven activity from actual policyholder behavior and evaluate each separately whenever possible.

With the introduction of PBR under VM-22 for fixed annuities, industry studies have become increasingly important for establishing credible and defensible assumptions, particularly regarding dynamic lapse rates. These studies not only support alignment with regulatory expectations and peer practices but also play a critical role in informing the selection and justification of Provision for Adverse Deviation (PADs) and ensuring that appropriate margins for conservatism are maintained within reserve methodologies. Ultimately, a balanced approach that leverages both industry intelligence and company-specific experience is essential for robust risk management and regulatory compliance in the evolving reserving landscape.

Our analysis emphasizes the complexity of modeling and understanding the dynamic lapse behavior on FIA. A separate, recent industry survey on dynamic lapses that Milliman performed shows results that further underscore the considerable diversity in dynamic lapse assumption practices across insurers, reflecting differences in product design, distribution, and internal experience credibility. Surveyed companies report a wide range of sensitivity parameters and modeling approaches, highlighting both the challenge and importance of calibrating assumptions to company-specific circumstances. Notably, some insurers are adopting advanced scenario-based and stochastic methods to better capture the complexities of policyholder behavior in evolving interest rate environments. These trends, alongside increasing regulatory attention and peer benchmarking, reinforce the need for ongoing review and enhancement of dynamic lapse modeling frameworks. Incorporating insights from industry surveys can help companies identify emerging best practices and benchmark their own approaches. Ultimately, robust assumption setting should still balance industry intelligence with the unique attributes and experience of each insurer’s block of business, and this paper provides some insights into how companies can accomplish this.

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