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Know Your Policyholders First, Model Their Behavior Second

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Author's note: This article applies to all kinds of policyholder behavior, including, but not limited to, lapses/surrenders, premium persistency, partial withdrawals, policy loan take-ups, and buy-back take-ups. However, for the ease of presentation, lapse from a contract with cash surrender value is the focus of the discussion.

Actuaries have traditionally determined the lapse assumption by studying how many policies have lapsed out of the entire product portfolio over time. This analysis is then split over dimensions such as policy duration, distribution channel, etc., which then drives a typical lapse assumption.

Some products offer significant guaranteed benefits, such as the living benefit riders on variable annuities (VA). The lapse assumption for these products typically involves a dynamic function in the sense that lapse rates can be affected by external market conditions such as equity market movements or interest rate changes. The formulation of the dynamic function revolves around our view as actuaries of the perceived value of the insurance benefits (including the guarantees) to the policyholders. A typical example in the case of VA is where we expect, when the equity markets experience low returns or losses, that the underlying guarantee becomes more valuable and therefore the policyholders will hold on to the contract. We sometimes would claim that policyholders behave irrationally if the actual experience deviates from that expectation.

We can defend our lapse assumption using a traditional “A over E” analysis, which compares actual experience with the expected assumption. It serves as a useful check on our assumption being consistent with the actual experience.



That said, there are still challenges when we try to formulate a lapse assumption in some unprecedented environments. For example, what would happen with the fixed annuity lapse if interest rates go up a lot, and very quickly, or more generally how would policyholders behave in extreme tail event scenarios? It is hard to answer questions like these when there is very little or no historical data that mimic such unprecedented environments. In situations like these, we fall back to what we do best: apply actuarial judgment.

But is actuarial judgment really useful in these situations? Undeniably, with our training, actuaries are better positioned than most others to understand the mechanics of insurance products. However, perhaps the very fact that we know so much about the mechanics of insurance products makes us ill-positioned to speculate on how less knowledgeable policyholders would behave. Our assumptions may be more geared towards how we would behave, as a fully informed individual. This “self-selection” offers little guidance about how an individual with lesser technical knowledge that owns the same insurance products would behave.

As a simple example, my wife is not an actuary, and she owns a whole life insurance policy that offers a cash surrender value that is linked to the insurance company’s investment performance. When I asked her when she might surrender and cash in, her response was either when kids go to college or when we retire. In either case, there is a need for some big lump sum cash that will cover more than our daily expenditure. When I asked her about how the insurance product works and how she expects the company will credit return on the policy, she has no idea. My wife has no actuarial training, but she studied finance and used to work at a reputable investment bank. Nevertheless, it is clear that her thinking about when to lapse has little to do with how the underlying value of the contract works, and instead is driven almost exclusively by the family needs for money. It is very likely that such needs may change over time as the financial condition and/or spending needs of our household changes, but fundamentally the time when she thinks about surrendering the policy is when she or the family needs the money.

Now if we look at this issue from a broader perspective, an insurance company has many policyholders of the same age and gender that have purchased the same insurance product from the same distribution channel around the same time. Today, we typically assume that they behave the same way in terms of lapsing the policy. In reality, however, two female policyholders both at age 45 can live a very different life: one married and the other single; one owns the house and the other rents; their jobs and income level can differ significantly; or their health condition may differ. Therefore, their need to access the insurance policy for additional cash is likely to differ significantly too.

Traditionally, an actuarial projection only requires us to have a reasonably good estimate of the overall lapse from any particular product. There is, therefore, no need for actuaries to know more about individual policyholders. An overall estimate averages out the different behavior patterns from different policyholders. However, when unprecedented conditions arise, whether individual, household, or economic, individuals respond differently, and our overall estimates start to be less accurate, possibly to the point of failing.

During the financial crisis of 2008–2009, account values of most VA contracts reduced significantly, resulting in the underlying living benefit guarantees becoming much more valuable. This would predict a reduced lapse rate under a typical actuarial lapse assumption for VA. However, the Milliman VALUES study, an industry-level experience study on VA products, shows that during the financial crisis the actual observed lapses far exceeded the expected from such a lapse assumption, as shown in Figure 1.

Figure 1
Lapse During Financial Crisis

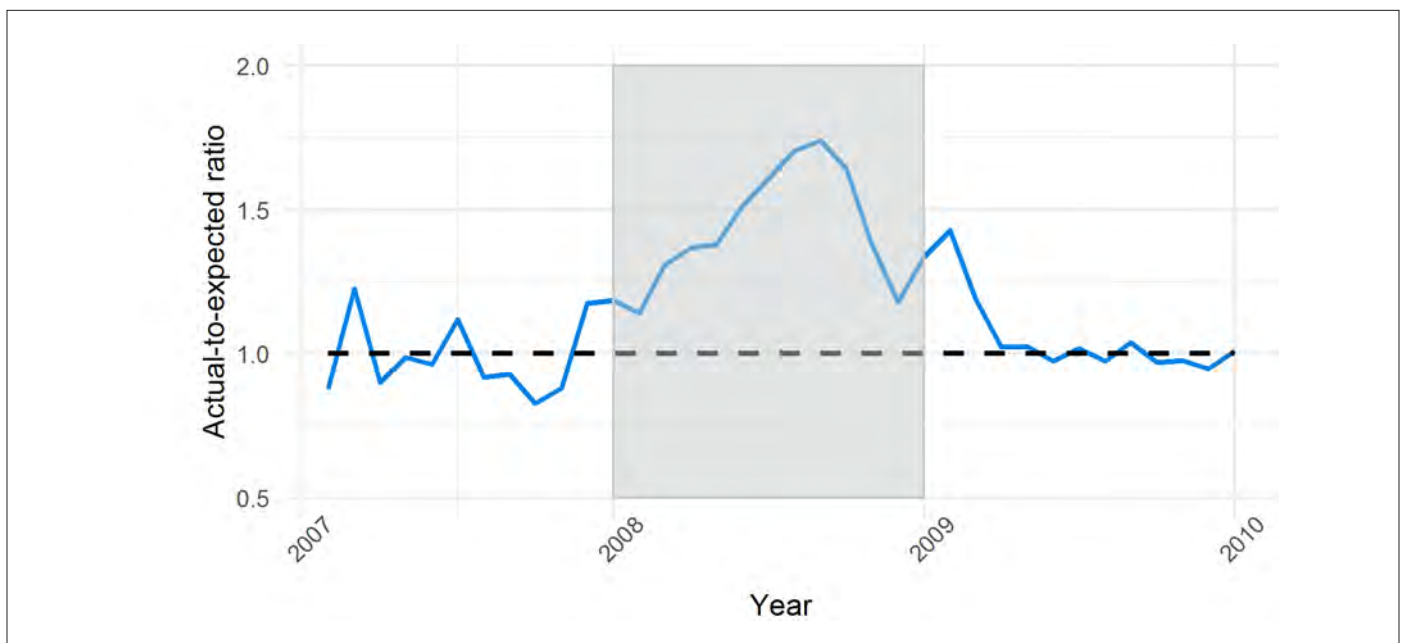
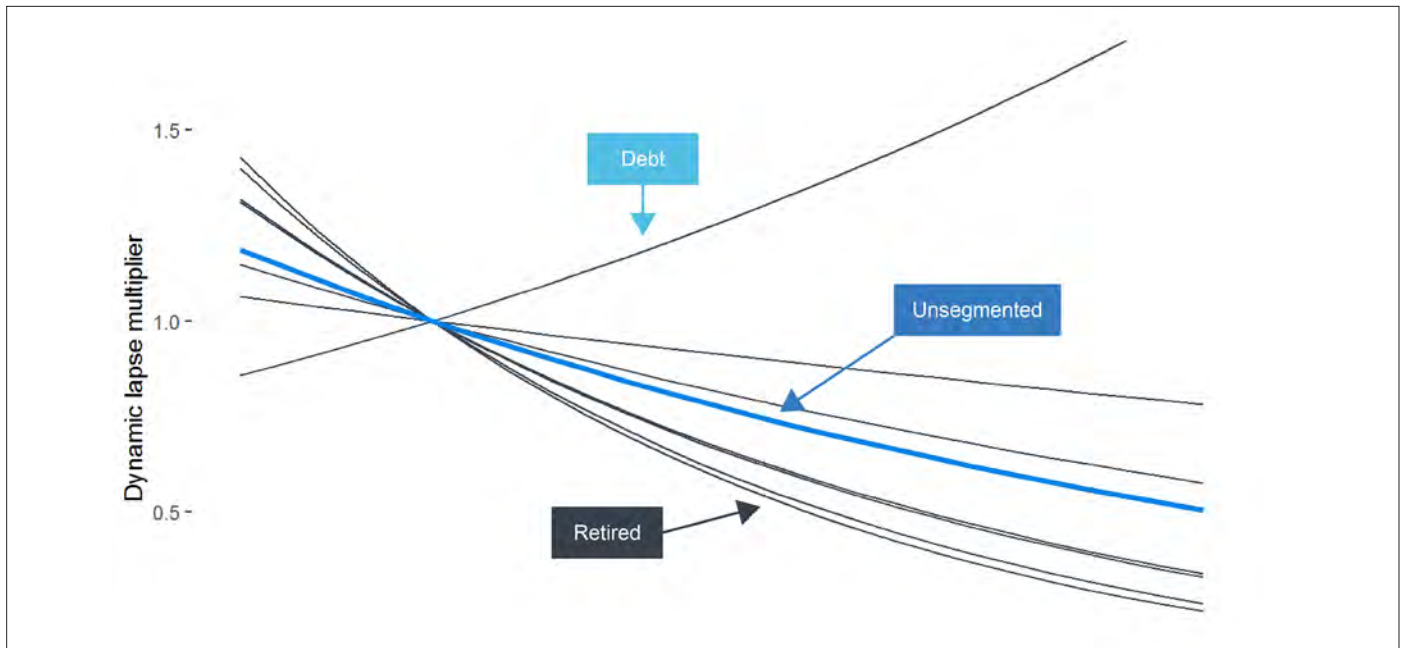


Figure 2
Segmented Lapse Model



Another Milliman research project collected a more granular set of data to help understand policyholders better, including data related to mortgage, household income, credit, family demographics, etc. The policyholders were divided into different profiles according to these underlying characteristics as well as how they have behaved differently with their insurance policies. Figure 2 shows a handful of profiles highlighting how different policyholder characteristics can mean a different response to changes in the underlying value of the guarantees in their propensity to lapse prediction. The X-axis shows the moneyness of the guarantees, which is the ratio of the guarantee over the account value. The larger the ratio, the more valuable the guarantees. The y-axis shows the multiplier to the base lapse rates corresponding to the different moneynesses. Each line represents behavior from a different profile, with the blue line representing the average behavior across all policyholders.

In particular, those in what is characterized as the “Debt” profile, defined by individuals with relatively lower credit scores and larger debts and possibly recent delinquencies, would in fact be more likely to lapse when the guarantee is worth more relative to the account value. During the financial crisis of 2008–2009, those in the Debt profile would likely have experienced rapidly increasing liquidity needs and therefore would have sought access to cash within all their available resources. Thus, the lapse propensity of this group increased significantly relative to a typical lapse assumption’s expectations, and relative to other policyholder profiles. Conversely, those in what is characterized as the “Retired” profile, defined by individuals that tend to be older, retired, and live in neighborhoods with people of similar age and

characteristics, would be least likely to lapse when the guarantee is worth more.

Had we been able to obtain similar big data during the financial crisis, we would have been able to identify those that had increased needs for liquidity and were thus more likely to lapse, regardless of the value of the underlying guarantee. That would then have allowed us to have a better assumption that would be more consistent with the actual observation during the financial crisis.

This approach enables actuaries to know and understand the policyholders first, and then model their behavior. Actuaries can start to embrace the power of big data to understand and monitor the changing liquidity needs of the policyholders. As market conditions change, or even start to slide into uncharted waters such as the financial crisis in 2008 or the pandemic we are experiencing right now, big data can serve as leading indicators to tell us whether policyholders’ needs to access liquidity from their insurance policies would increase.

This approach of big-data-driven analytics into individual-level policyholder behavior also enables us to more accurately determine the profitability from each policyholder. With profitability mapped at the individual policyholder level, life insurance companies will be able to deploy business strategies based on policy-level information instead of product-level information. This offers a new lever for insurers to manage their risk, unlock profitability, and ultimately better protect the wellbeing of their customers in the long term.

Retention strategy, buy-back (typically in the annuity space), and asset-liability management (ALM) are some examples of the in-force management strategies insurance companies have employed. With the policy-level information, a retention strategy can be better designed with trade-off analysis between the long-term profitability of each policy and its short-term propensity to lapse. A buy-back strategy can be optimized by understanding how people will respond differently to the offer. An ALM strategy may be modified to group policyholders with similar propensity to lapse, which may serve as a guide to invest in illiquid assets with extra yields.

On the new business side, understanding how policyholders may behave differently could suggest a need to change the product design to better suit certain policyholders. Of course, policyholder behavior is also a function of the distributors and advisors. By mapping the profitability of new business to the individual level, it allows insurers to monitor the performance of distributors not only by the top line (their sales volume) but also by the bottom line (the profitability of business).

Big-data-driven analytics are now being used by life insurance companies in marketing and underwriting, but they have not been employed by actuaries to nearly the same extent to understand our policyholders. Let us not forget that each insurance contract we work with every day is not simply a record or a model point. Behind every insurance contract is a real individual, and each has a different story that motivated their purchase of the insurance contract. We will never have the luxury of listening to every story they would tell, but we can attempt to understand the general narratives a bit better using the data. Know your customer, and then model their behavior. ■



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