Milliman Research Report

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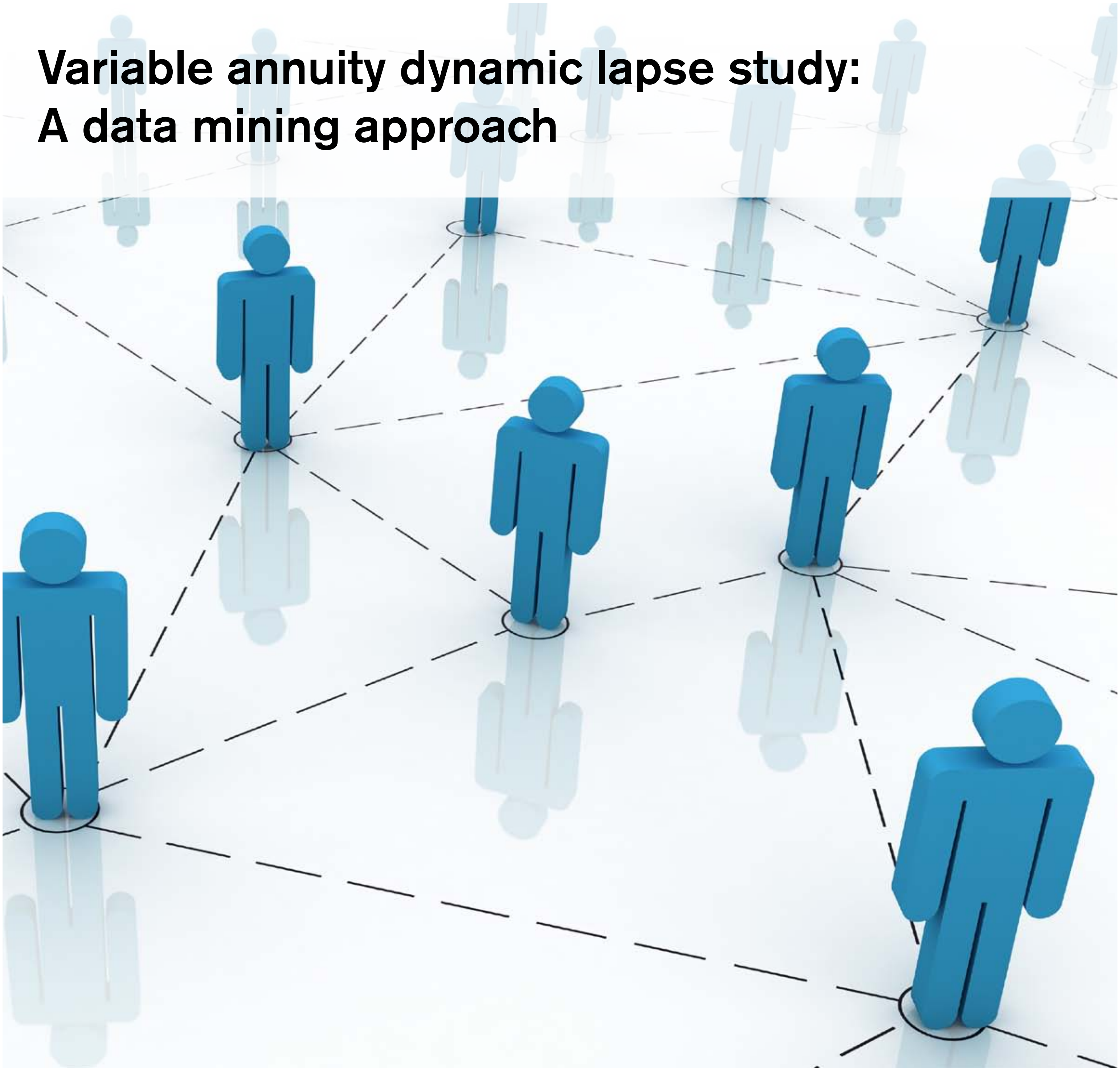
Variable annuity dynamic lapse study: A data mining approach



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EXECUTIVE SUMMARY

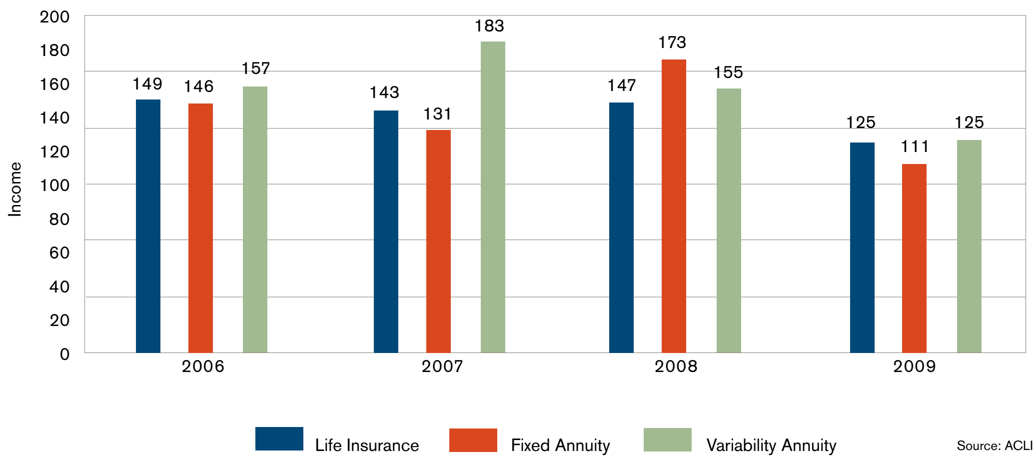
Dynamic lapse behavior is an important factor in variable annuity (VA) pricing and valuation. A company can regularly collect lapse data to form the basis for data mining, which can lead to fundamental insights on policy lapse behavior.

This paper describes the issues to be considered in the data-mining process using a realistic illustrative example. It explores the issues of data credibility, relevance, and formula fitting.

BACKGROUND

Over the past couple of decades, VAs have become more and more important to the life insurance industry. Starting in 1986, annuity premiums have surpassed life insurance premiums for life insurance companies. Over the past decade, the VA section experienced tremendous growth, and now the life insurance industry is roughly divided equally among life insurance, fixed annuities, and VAs. The graph in Figure 1 shows the trend from 2006 through 2009.

FIGURE 1: ANNUAL PREMIUM INCOME BY TYPE OF CONTRACTS ($BILLION)



Source: ACLI

Historically, life insurance companies have been deriving their profits from two major sources: actuarial experience and investment elements. The actuarial experience includes mortality and morbidity margins. The investment elements include the spread and fees life insurance companies charge based on the assets invested in insurance policies.

The life insurance industry has developed systematic approaches to measure and control the actuarial experiences over the past 100 years. As a result, the industry has a pretty good grasp of actuarial experiences. The actuarial claims from even major disasters such as the September 11 terrorist attacks did not cause undue hardship to the life insurance industry. On the other hand, products purely designed to provide protection against mortality or morbidity can quickly become commoditized, resulting in intense competition among market participants.

The investment element, on the other hand, appears to provide life insurance companies with a much wider range of product designs and potential for profit. Compared with other investment options, life insurance products enjoy the benefit of preferential tax treatment, where investment income within a life insurance product is tax deferred. From universal life to fixed annuities to VAs, the life insurance industry has been relying more and more on the investment elements.

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A VA contract is a product that heavily relies on the investment elements. It is essentially a collection of mutual funds wrapped within an annuity contract. One major competitive advantage of VAs over mutual funds is that many VA products include minimum guarantees, as shown in the table in Figure 2.

FIGURE 2: VA MINIMUM GUARANTEES

MINIMUM GUARANTEE BENEFITS	DESCRIPTION
GUARANTEED MINIMUM DEATH BENEFIT (GMDB)	A MINIMUM FUND VALUE UPON DEATH
GUARANTEED MINIMUM ACCUMULATION BENEFIT (GMAB)	A MINIMUM FUND VALUE UPON SURVIVORSHIP TO SPECIFIED DURATION OR AGE
GUARANTEED MINIMUM INCOME BENEFIT (GMIB)	A MINIMUM ANNUITY INCOME LEVEL UPON ANNUITIZATION AT A SPECIFIED AGE OR DURATION
GUARANTEED MINIMUM WITHDRAWAL BENEFIT (GMWB)	A MINIMUM WITHDRAWAL AMOUNT FOR A FIXED TERM
GUARANTEED LIFETIME WITHDRAWAL BENEFIT (GLWB)	A MINIMUM WITHDRAWAL AMOUNT FOR LIFE

While the minimum guarantees differentiate VA writers from regular mutual fund providers, they also expose VA writers to significant capital market risks because the minimum guarantees are in essence financial put options. As a result, all major VA writers have implemented some form of hedging program to mitigate their capital market exposures.

An important assumption in the hedging programs involves the policyholder lapses used in the valuation process in the hedging programs.

An important assumption in the hedging programs involves the policyholder lapses used in the valuation process in the hedging programs. The lapse assumption affects the financial outcome in two major areas. The first is with the guarantee payoff. The second is with the fee income.

An increase in lapses in a cohort of insured would leave fewer insured to ultimately make a claim on the guarantees, and is therefore beneficial to the insurer in this regard. However, an increase in lapses also reduces the fees the insurer can collect, and is therefore detrimental to the insurer in this regard.

A further complication is that policyholder lapse behavior is also a function of capital market performance, which is referred to as dynamic lapse behavior. This paper examines how dynamic lapse affects the performance of VA products and how to determine the dynamic lapse assumptions.

IMPORTANCE OF DYNAMIC LAPSE ASSUMPTION

Lapse and dynamic lapse assumptions are a critical part of pricing and valuation of VA guarantees. We will discuss the effect of these assumptions in this section.

In order to understand the impact of lapse and dynamic lapse assumptions on VA contracts, it is necessary to have a high-level understanding of the nature of lapses. In VAs the term “lapse” has been used interchangeably with “surrender.” There are, in fact, subtle but important differences.

The term “lapse” came from the world of traditional insurance contracts, where the policyholder agrees to pay a periodic premium for insurance coverage. If the policyholder fails to make the periodic payment for some time, then the insurance policy becomes void, and the policy “lapses.” Here the policyholder needs to take the action of paying the premium in order to keep the policy in force, and inaction leads to a policy lapse.

The “surrender” of a VA contract is different. In major VA markets such as the United States and Japan, most VA contracts are sold as single-premium contracts where a large initial premium is paid. Although subsequent payments of premium are often allowed, they are not needed to keep the VA contract in force. Even for regular-premium VA contracts, non-payment of scheduled premiums generally does not lead to the cancellation of the VA contract.

If a policyholder wants to terminate his or her VA contract, the policyholder has to contact the VA writer and go through a certain process before the VA contract can be terminated. In other words, the surrendering of a VA contract requires conscious actions from the policyholder. In addition, insurance companies often charge a surrender penalty if the surrender happens in early years of the contract, in an effort to recover the acquisition expenses incurred at sale. A typical B-share product has a seven-year surrender penalty schedule, with the level of the charge diminishing toward the end of the seven-year period.

Because of this characteristic of VA contracts, one would expect relatively low lapse rates in VA contracts. When a person purchases a VA contract, he or she is presumably convinced of the value of the contract and expects to hold the contract for some period of time. However, uncertainties in the policyholder’s life may force the policyholder to surrender the VA contract to meet his or her current liquidity needs. When this happens, the policyholder’s cash needs outweigh any potential losses from the surrender. In a cohort of VA policyholders, this is the basis for minimum lapse rates. The minimum lapse rates vary from cohort to cohort, but they generally have low values, such as from 0.5% to 2% per year.

The other side of the coin is that VA is an investment product, and an investor’s goal is to seek the highest possible returns. As such, a VA policyholder is likely to compare the investment performance of the VA contract with available alternatives. If there are alternatives that appear to provide better performance that outweighs the loss of surrendering the policy, the policyholder is likely to take action to surrender the policy to invest in the alternative. This is the origin of dynamic lapse behavior in a cohort of VA policyholders.

If there are alternatives that appear to provide better performance that outweighs the loss of surrendering the policy, the policyholder is likely to take action to surrender the policy to invest in the alternative. This is the origin of dynamic lapse behavior in a cohort of VA policyholders.

We will examine the impact of static lapse rates and dynamic lapse behavior separately in this section.

As the minimum guarantees are in essence financial put options, Monte Carlo simulation is a universally appropriate method to price and value the guarantees. There are, however, simplified situations where close-form analytic solutions exist. Although the close-form analytic solutions are rare, they can serve to validate the Monte Carlo simulation and provide useful insight into how various factor impact the pricing and valuation process.

The following example illustrates the process. Below are the assumptions behind a GMAB guarantee.

Benefit type:	**GMAB**
Benefit term (Bt):	**10 years**
Initial premium (Ip):	**$100,000**
Benefit balance (Bb):	**$100,000 (Return of premium design)**
Risk-free rate (Rf):	**flat 4%**
Fund volatility (Fv):	**flat 20%**
M&E fees (Me):	**2.5%**
Lapse rate (Lr):	**flat 5%**

For simplicity, no mortality is considered.

Then the present value (PV) of the GMAB claim is PVclaim = ((1- Lr)^Bt * BS (Ip, Bb, Rf, Rf – Me, Fv, Bt), where BS is the Black-Scholes put option price with

**BS (stock price,
strike price,
risk-free rate,
cost of carry,
volatility,
time to maturity)**

The present value of the account value (PVAV) is

PVAV = (1 – exp (-Me * Bt) * ((1-Lr)^Bt)) / (1 – exp (-Me) * (1-Lr))

Monte Carlo simulation over 10,000 stochastic scenarios leads to similar results. Given the above assumptions, the table in Figure 3 shows the results from the close form formula and the Monte Carlo simulation.

FIGURE 3: SIMULATION RESULTS

	ANALYTIC FORMULA	MONTE CARLO
PVCLAIM	$7,809	$7,719
PVAV	$726,566	$727,306
GUARANTEE COST	1.07%	1.06%

The guarantee cost is defined as a flat percentage of the account value and is calculated as PVClaim / PVAV.

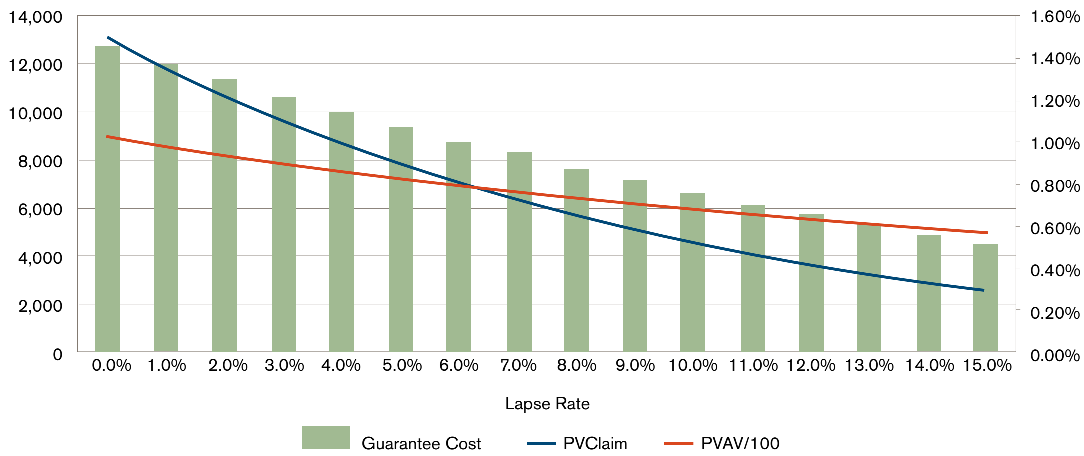
Based on the analytic formula, the table in Figure 4 is produced to illustrate the effect of lapse assumptions on the pricing and valuation of the GMAB guarantee.

FIGURE 4: EFFECTS OF LAPSE ASSUMPTIONS

LAPSE RATE	PVCLAIM	PVAV	GUARANTEE COST
0.0%	13,043	895,903	1.46%
1.0%	11,796	858,418	1.37%
2.0%	10,657	822,836	1.30%
3.0%	9,618	789,061	1.22%
4.0%	8,671	757,000	1.15%
5.0%	7,809	726,566	1.07%
6.0%	7,025	697,675	1.01%
7.0%	6,313	670,248	0.94%
8.0%	5,666	644,208	0.88%
9.0%	5,079	619,485	0.82%
10.0%	4,548	596,009	0.76%

The chart in Figure 5 is a graphic illustration of the results in the above table.

FIGURE 5: EFFECTS OF LAPSE RATES ON GUARANTEE VALUATIONS



Based on this set of results, one can make the following observations:

1. Lapse assumption is a critical part of guarantee pricing and valuation. Values can easily change by a factor of 50% with different lapse assumptions.

2. Increased lapse assumption tends to lead to reduced cost of the guarantee, where the reduction of potential claims outweighs the reduction in future account values and fees.

Because other types of minimum guarantees can be viewed as a series of GMAB benefits with different maturity terms, the observations above are generally true for other minimum guarantees as well.

While it is clear that increased lapses help the profitability for the minimum guarantee riders, the effect on the entire VA contract is not that straightforward. This is because there is usually an upfront commission paid by the VA writer at the sale of a VA contract. The VA writer hopes to collect M&E fees in the future to amortize the initial expenses. In effect, a VA writer has taken a leveraged position at the sale of the VA contract. Increased lapses will lead to reduced future account value, and therefore lower M&E fees collected by the VA writer. A sudden increase in lapses can result in future M&E fees level not being enough to fully amortize the initial cost of acquiring the policy.

Generally, minimum guarantee riders are not priced to bring profit to the VA writer. The profit margins of VA contracts still come from the M&E fees on the base VA contracts. The minimum guarantee riders are generally perceived by policyholders to provide additional value, and thereby reduce lapses overall, contributing to enhanced VA contract profitability.

We have examined the impact of static lapse assumptions on the cost of the minimum guarantees and the base VA contract. Now we will examine the impact of dynamic lapse behavior.

The dynamic lapse behavior is essentially a selection process of the policyholders against the VA writer. The general pattern is that more policies will lapse when the capital market is up, and fewer policies will lapse when the capital market is down.

In an up market, the value of the minimum guarantee diminishes as the account value is likely to exceed the minimum guarantee values. As such, surrendering the policy does not create much loss to the policyholder. Also, more alternative investments tend to become available in an up market.

The dynamic lapse behavior is essentially a selection process of the policyholders against the VA writer. The general pattern is that more policies will lapse when the capital market is up, and fewer policies will lapse when the capital market is down.

On the other hand, a down market can result in the surrender value being less than the guarantee value, causing the policy to be in-the-money. If the policyholder surrenders at this time, then he or she can only get the reduced surrender value, forfeiting the added value from the guarantee rider. The result is that there is strong incentive for the policyholder to keep the in-the-money VA contract in force.

Although the pattern of reduced lapses in a down market is generally true, there has been anecdotal evidence that surrender rates increased during the most severe months of the recent financial crisis. Even as a VA contract can be deeply in-the-money, and the policyholder would forfeit significant value in the minimum guarantee rider, the severe financial crisis may have left the policyholder in such a dire financial situation that he or she would desperately need any funds immediately available. Persons facing foreclosure on their homes probably would not care too much about guarantee values to be realized several years in the future.

Dynamic lapse behavior makes the cost of minimum guarantees higher and the amortization of initial acquisition cost more difficult.

Dynamic lapse behavior is costly to VA writers from many perspectives. Dynamic lapse behavior makes the cost of minimum guarantees higher and the amortization of initial acquisition cost more difficult.

Conceptually, in an up market, the minimum guarantee will have no value, and thus increased lapses do not reduce the guarantee claims. And yet the increased lapses would reduce the fees that can be collected when the account value, which is the basis for fees, is higher.

In a down market, the minimum guarantees will become in-the-money, and reduced lapses will leave more policyholders in force to make a claim on the minimum guarantees. Reduced lapses also increase the weight of scenarios in which collected fees are lower because of reduced account values.

There are policy designs where the guarantee fee charges are based on the guarantee amount instead of the account value. The purpose of these designs is to reduce the sensitivity of guarantee fees to dynamic lapse behavior by fixing the basis of fee charges. While this goal is achieved, this design also increases the sensitivity of claims to dynamic lapses, particularly in down markets.

This can be illustrated with a simple numerical example. Let's assume a GMAB with $100,000 initial premium and $100,000 GMAB balance is issued. Let's assume the account value (AV) experiences a 20% drop in a year and the 1% guarantee fee is taken out at the end of the year. If the guarantee fee is based on the account value, then the collected fee would be 1% * 100,000 * (1-20%) = 800, and the fee is impacted by the account value drop. The net amount at risk (NAR) for the GMAB is 100,000 – (80,000 – 800) = 20,200. On the other hand, if the guarantee fee is based on the GMAB balance, then the collected fee would be 1% * 100,000 = 1,000, which does not decrease with the account value. However, the NAR for this design would be 100,000 – (80,000 – 1,000) = 21,000, which is higher than the case with AV-based fees.

Dynamic lapse behavior also makes it more difficult to amortize the initial acquisition cost. Without dynamic lapse behavior, a writer would expect to collect more in M&E fees in up markets and less in down markets, with greater degree of certainty, and the fees would be enough for the amortization on average. The nature of dynamic lapse is such that there will be less in force in an up market leading to less in fees when the VA writer should be collecting more fees. On the other hand, there are more policies in force in a down market when the VA writer is not able to collect more fees.

The following simple example illustrates the impact of dynamic lapse behavior. Dynamic lapse behavior introduces an additional level of complexity in the pricing and valuation of the guarantees, and usually there is not a closed form analytic solution. Monte Carlo simulation is the standard method of calculation.

The example above with 5% flat lapse rate is the base case for comparison. To simulate dynamic lapse behavior, we use a simple binomial lapse function for illustration purposes. The binomial lapse function assumes the lapse rate is x% when the policy is out-of-the-money and y% when the policy is in-the-money. In order for the dynamic lapse results to be comparable to the flat lapse base case, the binomial dynamic lapse function is designed such that the average ultimate survival rate is the same as the flat lapse rate base case.

For example, a combination of x = 5.53% and y = 4.53% results in the same average survival rate as the 5% flat lapse case. The difference between x and y can be seen as the sensitivity or strength of the dynamic lapse behavior.

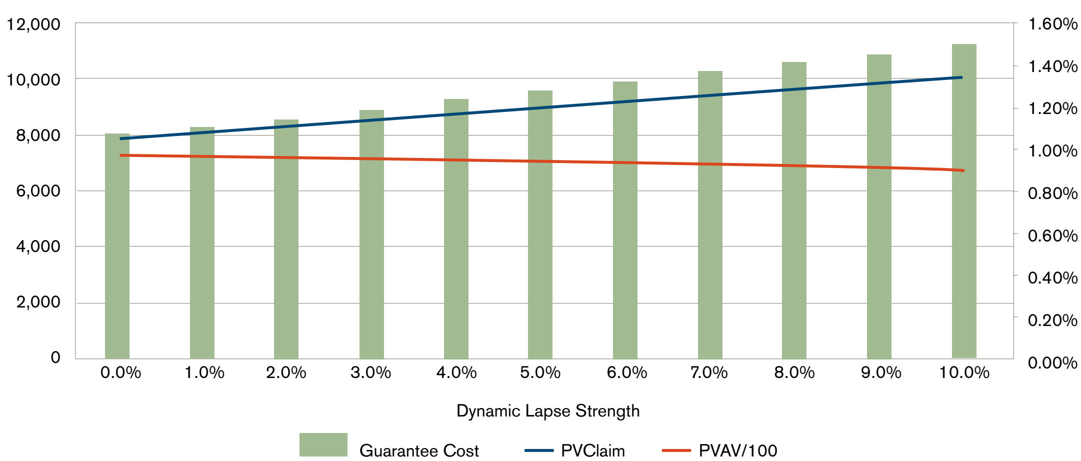
The table in Figure 6 summarizes the pricing and valuation results with various dynamic lapse strength.

FIGURE 6: PRICING AND VALUATION RESULTS OF DYNAMIC LAPSE STRENGTH

DYNAMIC LAPSE STRENGTH	PVCLAIM	PVAV/100	GUARANTEE COST
0.0%	7,809	7,266	1.07%
1.0%	7,981	7,230	1.10%
2.0%	8,240	7,183	1.15%
3.0%	8,493	7,134	1.19%
4.0%	8,740	7,083	1.23%
5.0%	8,980	7,028	1.28%
6.0%	9,214	6,972	1.32%
7.0%	9,440	6,913	1.37%
8.0%	9,658	6,853	1.41%
9.0%	9,869	6,791	1.45%
10.0%	10,072	6,728	1.50%

The chart in Figure 7 graphically illustrates the impact of dynamic lapse strength.

FIGURE 7: IMPACTS OF DYNAMIC LAPSE STRENGTH



From the data above, it is clear that, on average, dynamic lapse behavior increases claims and reduces the account values and fees collected, therefore leading to higher costs for the guarantees.

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As the term of the VA guarantee becomes longer, the cumulative effect of dynamic lapse becomes more significant.

Different product designs also result in different sensitivities to dynamic lapse behavior. One example is the term of the product. As the term of the VA guarantee becomes longer, the cumulative effect of dynamic lapse becomes more significant. The table in Figure 8 compares the guarantee cost of a 10-year GMAB and a 20-year GMAB with otherwise identical designs. It is clear that the 20-year term has greater sensitivity to the dynamic lapse strength than the 10-year term, as the guarantee cost increases by 78% in the 20-year term design instead of the 39% increase in the 10-year term design.

FIGURE 8: DYNAMIC LAPSE STRENGTH COSTS ACROSS GMAB TERMS

DYNAMIC LAPSE STRENGTH	10-YEAR GUARANTEE COST	20-YEAR GUARANTEE COST
0.0%	1.07%	0.38%
1.0%	1.10%	0.41%
2.0%	1.15%	0.44%
3.0%	1.19%	0.47%
4.0%	1.23%	0.50%
5.0%	1.28%	0.53%
6.0%	1.32%	0.56%
7.0%	1.37%	0.59%
8.0%	1.41%	0.62%
9.0%	1.45%	0.65%
10.0%	1.50%	0.68%

These examples illustrate that both the level of lapses and the strength of dynamic lapses are important factors in the financial performance of VA products with guarantees.

ILLUSTRATIVE DATA MINING

Despite the importance of lapse and dynamic lapse assumptions in the pricing and valuation of VA contracts, much of the work in determining these assumptions was a matter of educated guessing for many years because of a lack of historical data. In particular, it has been suspected that dynamic lapse behavior will be heavily influenced by the moneyness of VA contracts, but it is impossible to experiment with different levels of moneyness without market oscillation.

The situation has improved in the past couple of years. As VA writers continue to issue VA contracts, many years of experience have been accumulated. In addition, the market gyration in the past several years has resulted in many VA policies experiencing a wide range of moneyness.

With this wealth of data, large VA writers are in a position to utilize modern data-mining technology to study policyholder behaviors, including dynamic lapse activities. Data mining is the process of determining patterns from large amounts of data by using methods from statistics, optimization, and database management. Data mining has played an increasingly important role in modern business in obtaining better understanding of business result drivers. It is currently being used in a wide range of profiling practices, such as marketing, consumer behavior modeling, surveillance, and fraud detection.

Milliman has been performing hedging programs for VA writers on an outsourced basis for many years. Currently, Milliman manages the hedging programs for 32 companies with assets under management (AUM) of about $58 billion. There are about 5 million policies being regularly valuated. As part of the hedging program, Milliman receives regular in-force extracts on monthly or weekly bases. Over the years, Milliman has observed important patterns of dynamic lapse behaviors and developed general data-mining approaches to determine factors impacting dynamic lapses.

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To illustrate the data-mining processes, a hypothetical test in-force block of GMAB business is constructed. The test in-force block is not based on any one specific company's data, but it does reflect the general patterns that Milliman has observed over a large number of VA in-force policies.

Here is a basic description of this block of business:

- Year issued: 2006
- Observation period: Five years between 2006 and 2010
- Product design: Return of premium (ROP) GMDB and GMAB
- Surrender charge: Seven years at 7%, 6%, 5%, 4%, 3%, 2%, and 1% of account value
- Number of policies within the test in-force block: 100,000
- Data update frequency: Weekly

As such, we have more than 25 million data points within the study. The block of in-force policies also had a mixture of investments that resulted in moneyness as measured by the ratio of cash surrender value to guarantee amount of between 72% and 118%. This is a fairly wide range of moneyness and is a result of the economic environment between 2006 and 2010.

There are many statistical and database tools that can be used for data-mining purposes. For smaller data sets, Microsoft Office-based tools such as Access and Excel are sufficient. For larger data sets, more powerful tools are needed. Given the large amount of data points in our study, a combination of R and Excel-based tools were used.

In data-mining exercises, there are several fundamental questions to be answered:

- Is the data set credible?
- What variables are relevant?
- Are relevant variables causes or effects?
- What functions are the best to describe the dynamic behavior?

There are two layers of the data credibility issue. First of all, does the data set contain such material administrative errors that the data is not usable? This is essentially a question for policy administrative systems. For a hedging program, a VA writer must be able to provide detailed policy-by-policy in-force extracts on a regular basis. Because these in-force extracts are the basis for valuation in a hedging program, the ability to provide reliable data is a prerequisite for VA hedging program execution. Because the test data for this study is based on actual hedging programs, the administrative reliability is established.

Second, is the data set large enough to produce statistically significant results? There are numerous studies establishing the size of data sets for a given statistical significance level. However, these methods are often not easy to apply in practice. Empirical studies are often used instead. One approach is to arbitrarily split the data set into two parts of equal size. The planned analysis is then performed on the two halves of the data set as well as the entire data set. If the three results are close enough to each other, one can be reasonably sure that the size of the data set is large enough.

For example, the table in Figure 9 shows the results of lapses by policy duration and half in-force blocks. This table indicates that the observations made based on the aggregate data set and the half data sets are quite close, thus giving us confidence that the aggregate data set is large enough to produce credible results.

FIGURE 9: RESULTS OF LAPSES BY POLICY DURATION

	LAPSE RATES		
DURATION	**AGGREGATE**	**FIRST HALF DATA**	**SECOND HALF DATA**
1	1.27%	1.14%	1.40%
2	2.89%	2.83%	2.96%
3	2.12%	2.17%	2.07%
4	1.51%	1.55%	1.47%
5	1.79%	1.88%	1.70%
6	1.42%	1.43%	1.42%

Given the large amount of data, one has to decide which variables are useful contributing factors and which variables are irrelevant. The natural criterion for relevance is whether the results change when a variable is changed.

In data-mining exercises, relevance study can often lead to unexpected discoveries that reveal fundamental insights.

Relevance study should be performed on as many variables as possible, preferably on all variables. In data-mining exercises, relevance study can often lead to unexpected discoveries that reveal fundamental insights.

In his book *Outliers*, Malcolm Gladwell described a phenomenon that the birth months of top Canadian hockey players are disproportionally concentrated in the early months of the year, particularly in January. In-depth investigation of this phenomenon reveals that, because youth hockey leagues determine eligibility by calendar year, children born in January play in the same league as those born in December in the same calendar year. Because children born earlier in the year are further developed and more mature than their younger competitors, they are often identified as better athletes, leading to extra coaching and practice and a higher likelihood of selection for elite hockey leagues, which leads to even more coaching and practice.

This example illustrates two characteristics of relevance study: that there can often be unexpected relevant variables, and that relevance itself is not enough. The insight behind the relevance is more revealing.

In the case of the elite hokey players, Gladwell described how the birth month pattern was “accidentally” discovered by looking through the rosters of hockey teams. In fact, this pattern can be revealed through standard data-mining procedure. If the personal information about all hockey players is available, one can perform relevance study on all available data such as weight, height, birth month, birthday, number of siblings, etc. Many of the variables would turn out to be irrelevant, but the birth month pattern would emerge.

However, the birth month pattern alone is not enough to draw reasonable conclusions. It was only after careful research that the true cause of the January phenomenon was revealed, and the revelation can lead to actionable plans.

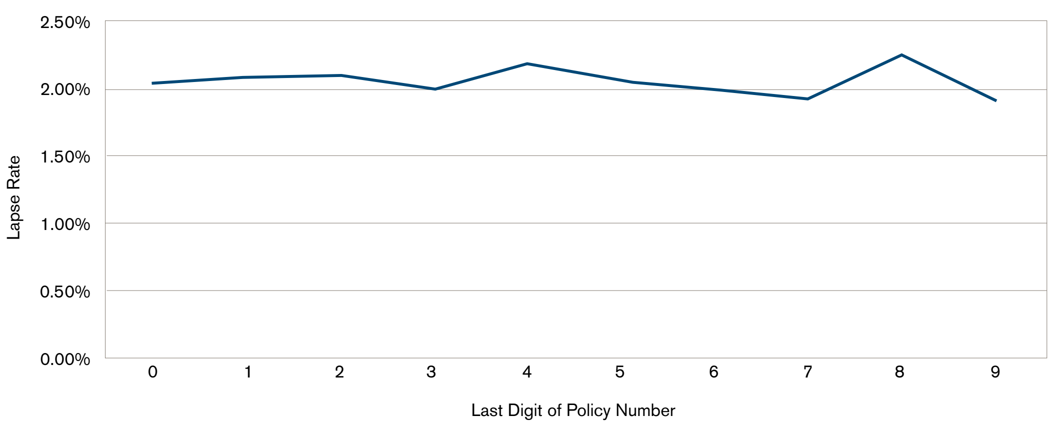
As an example, we have performed relevance study of lapse behavior on the last digit of policy numbers and on policy months. The results are shown in the table in Figure 10.

FIGURE 10: RELEVANCE STUDY OF LAPSE BEHAVIOR

LAST DIGIT OF POLICY NUMBER	LAPSE RATE
0	2.05%
1	2.11%
2	2.11%
3	2.02%
4	2.20%
5	2.07%
6	2.00%
7	1.93%
8	2.26%
9	1.92%

The relationship between lapse rates and the last digits of policy numbers is also shown in the graph in Figure 11. It is quite clear from the graph that the lapse rates do not vary with the last digit of policy numbers. As such, one can conclude that the last digit of policy numbers is irrelevant to lapse rates.

FIGURE 11: LAPSE RATES BY LAST DIGITS OF POLICY NUMBERS



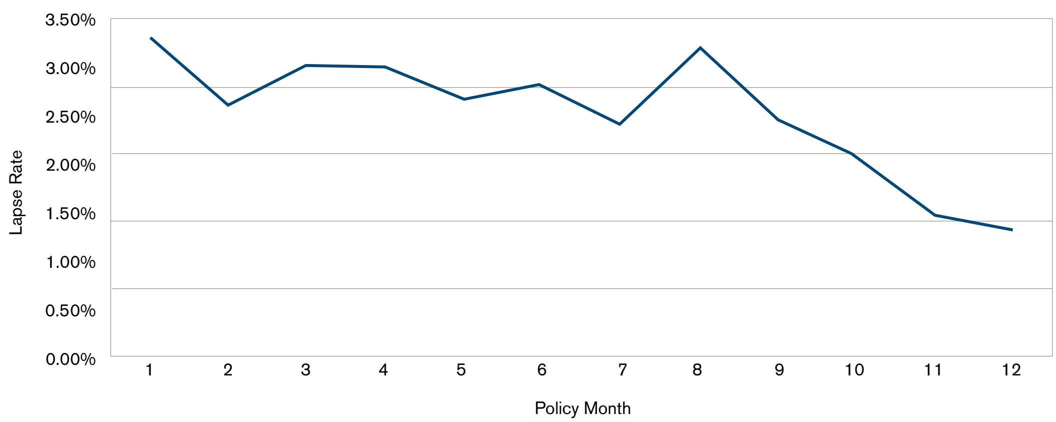
A similar study is performed on policy month. The policy month is the number of months since a policy's last anniversary. For example, if the duration between a policy's in-force date and its issue date is three years and seven months, then the policy month for this policy is 7. The lapse study results are shown in Figure 12 on the next page.

FIGURE 12: LAPSE RATES BY POLICY MONTH

POLICY MONTH	LAPSE RATE
1	3.27%
2	2.59%
3	3.01%
4	3.02%
5	2.68%
6	2.79%
7	2.39%
8	3.18%
9	2.44%
10	2.12%
11	1.46%
12	1.34%

The relationship between policy month and lapse rates is illustrated in the graph in Figure 13.

FIGURE 13: LAPSE RATES BY POLICY MONTH



Clearly a pattern has emerged between policy month and lapse rates. Lapse rates reduce significantly in the latter half of the policy year. The lapse rate is the lowest in policy month 12, which is less than half that experienced in policy month 1, the highest. It can be safely concluded that policy month is a relevant variable to lapse rates.

As in the case of elite hockey players' birth months, just knowing that a variable is relevant is not enough. Instead, the relevance study should open the door to in-depth study that can provide useful insight. Further research into this set of data and comparison with similar data reveals that the pattern between policy month and lapse rate is driven by the discontinuous surrender charge schedule.

This block of business has a seven-year declining surrender charge schedule at 7%, 6%, 5%, 4%, 3%, 2%, and 1% of account value. The surrender charge rate changes at policy anniversary. A policyholder who intends to surrender has incentive to wait past the next policy anniversary to take advantage of the lower surrender charge. While this tendency is not very obvious in the first half of a policy year, the benefit becomes increasingly prominent in the second half of a policy year. In particular, a policyholder in the 12th policy month just has to wait for a few weeks before a lower surrender charge takes effect. That leads to the lowest surrender rates in the 12th policy month.

As the examples of last digit of policy number and policy month have shown, a comprehensive relevance study may find many variables to be non-contributing irrelevant ones, but the relevant variables can lead to studies that uncover dynamics and provide fundamental insights.

Additional relevance study has been performed on gender and size, and the results are shown below.

The variance of lapse rates by gender is shown in the table in Figure 14. It is apparent that the gender of policyholders is related to different lapse behavior, with male policyholders having noticeably higher lapse rates.

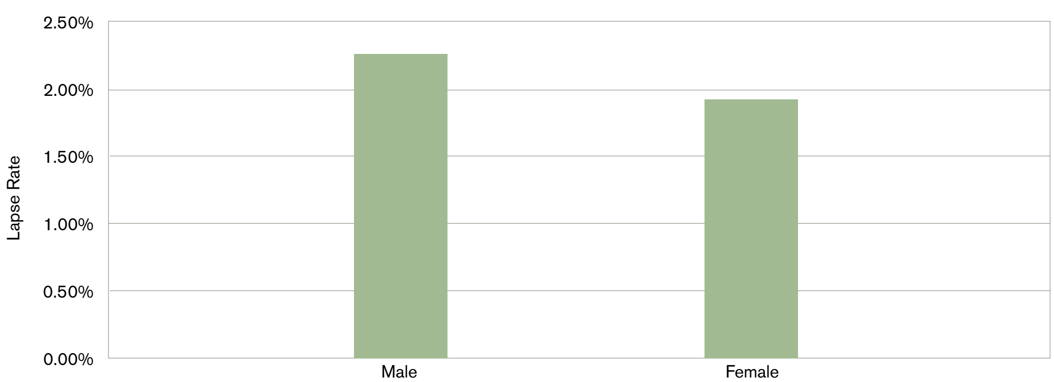
A comprehensive relevance study may find many variables to be non-contributing irrelevant ones, but the relevant variables can lead to studies that uncover dynamics and provide fundamental insights.

FIGURE 14: LAPSE RATES AND GENDER

GENDER	LAPSE RATE
MALE	2.31%
FEMALE	1.93%

The relationship between gender and lapse rates are shown in the chart in Figure 15. One plausible explanation of this pattern is different risk appetite between male and female policyholders.

FIGURE 15: LAPSE RATES AND GENDER



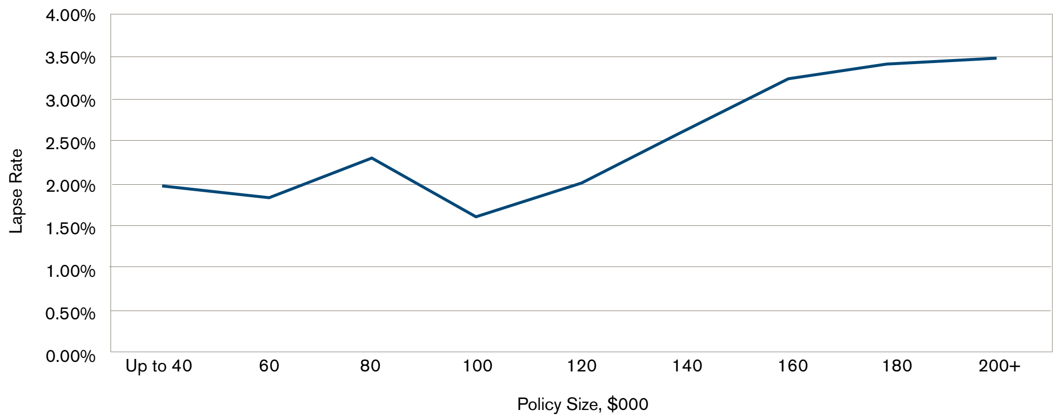
The variance of lapse rates by policy size is shown in the table in Figure 16. Policy size is defined as the initial policy deposit.

FIGURE 16: LAPSE RATES AND POLICY SIZE

POLICY SIZE ($000)	LAPSE RATE
UP TO 40	1.99%
60	1.87%
80	2.29%
100	1.61%
120	2.07%
140	2.63%
160	3.24%
180	3.43%
200+	3.46%

The relationship is shown in the graph in Figure 17.

FIGURE 17: LAPSE RATES AND POLICY SIZE



It is quite obvious that policy size is a contributing factor to policyholder lapse behavior, and that a larger policy size is related to higher surrender rates at the higher end. This behavior pattern is consistent with the fact that policyholders with larger sizes are more financially savvy and ready to seek out alternative investment vehicles when an opportunity arises. There are also more financial planners pitching other investment opportunity to policyholders with larger policy sizes, who tend to be financially better off. This pattern appears to have a cut-off size around $120 to $150. The pattern is pronounced above this cutoff size and not obvious below it.

Additional study is also performed on the relationship between gender and average size of policies. The results are shown in the table in Figure 18.

FIGURE 18: GENDER AND POLICY SIZE

GENDER	AVERAGE POLICY SIZE ($000)
MALE	80
FEMALE	64

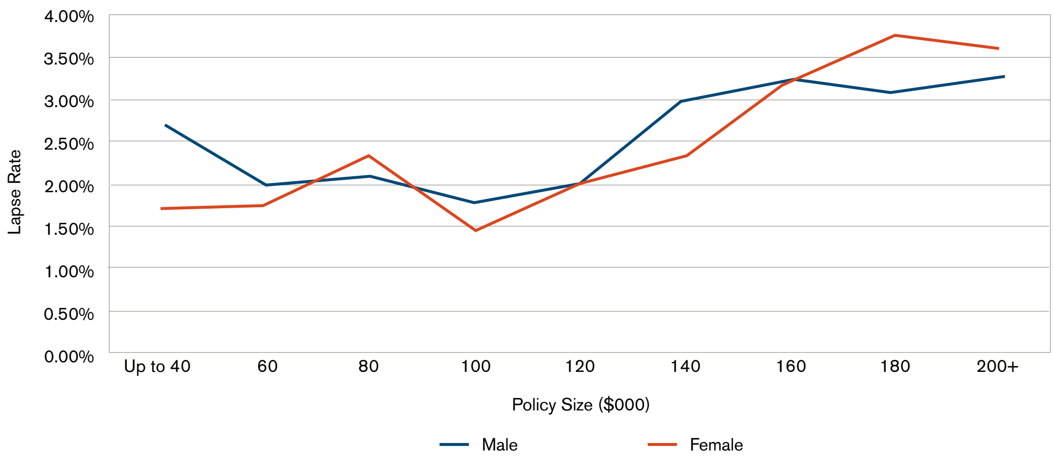
It is clear that from the table in Figure 18 that there is a material difference in policy size between male and female policyholders. This observation, combined with the fact that larger policies are more likely to surrender, raises the question of whether gender is indeed a contributing factor to lapse rates. To answer this question, further detailed study is performed by policy size and gender, and the results are shown in the table in Figure 19.

FIGURE 19: LAPSE RATES BY POLICY SIZE AND GENDER

	LAPSE RATE	
POLICY SIZE ($000)	MALE	FEMALE
UP TO 40	2.67%	1.73%
60	2.00%	1.79%
80	2.11%	2.39%
100	1.84%	1.47%
120	2.06%	2.07%
140	2.98%	2.36%
160	3.24%	3.24%
180	3.14%	3.77%
200+	3.26%	3.64%

The results are visually illustrated in the graph in Figure 20.

FIGURE 20: LAPSE RATES BY POLICY SIZE AND GENDER



From Figure 20, one can observe that there is not a consistent pattern between male and female policyholders given the same policy size. On the other hand, both male and female policies exhibit the trend that higher policies with larger sizes tend to have higher lapse rates.

Based on this observation, one can conclude that gender is in fact not a contributing factor to lapse rates. The different lapse rates between male and female policies are essentially driven by the difference in policy sizes between male and female policyholders. The plausible explanation that male and female policyholders have different financial risk appetite actually is not supported by the observed data.

This study of the relationships of gender and policy size with lapse rates further illustrates the application of relevancy study. Again, relevancy studies highlight that gender and policy size are useful variables for further study, and only detailed investigation would reveal that policy size is the actual driver for lapses.

Relevancy studies highlight that gender and policy size are useful variables for further study, and only detailed investigation would reveal that policy size is the actual driver for lapses.

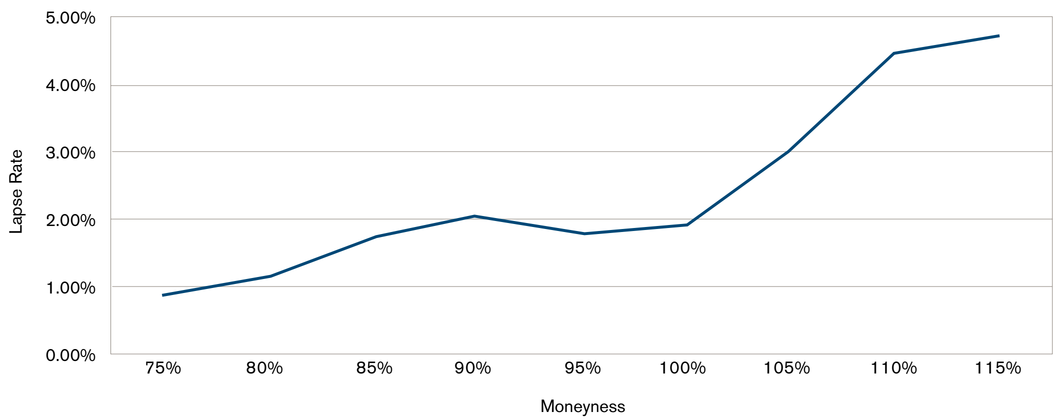
Naturally, one would expect the moneyness of a VA policy to be an important factor in its lapse behavior. The table in Figure 21 shows the relationship of moneyness with lapse rates, where the moneyness is defined as the ratio of cash surrender value to guarantee value.

FIGURE 21: LAPSE RATES AND MONEYNESS

MONEYNESS	LAPSE RATES
75%	0.91%
80%	1.23%
85%	1.78%
90%	2.05%
95%	1.84%
100%	1.93%
105%	3.10%
110%	4.49%
115%	4.72%

The relationship is visualized in the graph in Figure 22.

FIGURE 22: LAPSE RATES AND MONEYNESS



It is clear that moneyness is a variable that drives the lapse rates of this block of VA business. This observation is consistent with the VA industry's general expectation.

As in the study of gender and policy size, a combined study of moneyness and policy size is also performed, and the results are summarized in the table in Figure 23.

FIGURE 23: LAPSE RATES BY MONEYNESS AND POLICY SIZE

	LAPSE RATES BY MONEYNESS AND POLICY SIZE		
MONEYNESS	UP TO $80,000	$80,000 TO $150,000	$150,000+
75%	0.72%	1.12%	0.23%
80%	1.14%	1.27%	2.79%
85%	1.63%	1.90%	2.86%
90%	2.11%	1.68%	4.53%
95%	1.73%	1.94%	2.79%
100%	1.91%	1.79%	2.88%
105%	2.98%	2.76%	7.16%
110%	3.85%	5.03%	8.40%
115%	4.57%	3.73%	16.30%

The results are visualized in the graph in Figure 24.

FIGURE 24: LAPSE RATES BY MONEYNESS AND POLICY SIZE

From the graph, one can make the following observations:

- Both moneyness and policy size are contributing factors to lapse behavior.
- There is dynamic lapse behavior for all policy size cohorts.
- Dynamic lapse behavior is similar for policies with sizes below $150,000, but is noticeably higher for policies with sizes above $150,000.

Based on the observations above, it is most logical to separate the entire block of business into two cohorts, with sizes below and above $150,000. The results by this partition are shown in the table Figure 25.

FIGURE 25: LAPSE RATES BY MONEYNESS AND POLICY SIZE +/- $150,000

	LAPSE RATES BY MONEYNESS AND POLICY SIZE	
MONEYNESS	**$150,000-**	**$150,000+**
75%	1.00%	0.23%
80%	1.45%	2.79%
85%	2.05%	2.86%
90%	2.19%	4.53%
95%	1.94%	2.79%
100%	1.93%	2.88%
105%	3.33%	7.16%
110%	5.71%	8.40%
115%	5.90%	16.30%

This relationship is visualized in the graph in Figure 26.

FIGURE 26: LAPSE RATE BY MONEYNESS AND POLICY SIZE

It is not enough to simply know that certain variables are contributing factors. VA writers often need to mathematically model the lapse behavior.

It is not enough to simply know that certain variables are contributing factors. VA writers often need to mathematically model the lapse behavior. There are data-mining technologies that use algorithms to determine formulas that best fit the data available. Conceptually, this is an optimization process to select the forms of formula and parameters that minimize the error between the actual data and the fitted formula.

Because all function forms can be expressed as polynomial approximations, a polynomial form can be a good starting point in determining the ultimate form of the dynamic lapse function.

There are many forms of dynamic lapse formulas, such as exponential and tangential. In selecting a form, one has implicitly narrowed the scope of possible range of optimization. Because all function forms can be expressed as polynomial approximations, a polynomial form can be a good starting point in determining the ultimate form of the dynamic lapse function.

As an example, two third-order polynomials are fitted to the dynamic lapse data at different sizes. The sum of squared error is minimized.
Formulaically,

$L_f = a_0 + a_1 \cdot m + a_2 \cdot m^2 + a_3 \cdot m^3$
where
L_f is the formulaic dynamic lapse rate,
m is moneyness defined as the ratio of cash surrender value to guarantee value,
a_n are the parameters to be solved so that $\Sigma_{\text{all observation points}}(L_f - \text{actual lapse rate})^2$ is minimized.

The optimization results are summarized in the table in Figure 27.

FIGURE 27: PARAMETERS BY POLICY SIZE +/- $150,000

	POLICY SIZE	
PARAMETERS	**$150,000-**	**$150,000+**
a_0	-1.258	-0.980
a_1	4.300	3.941
a_2	-4.862	-5.172
a_3	1.846	2.258

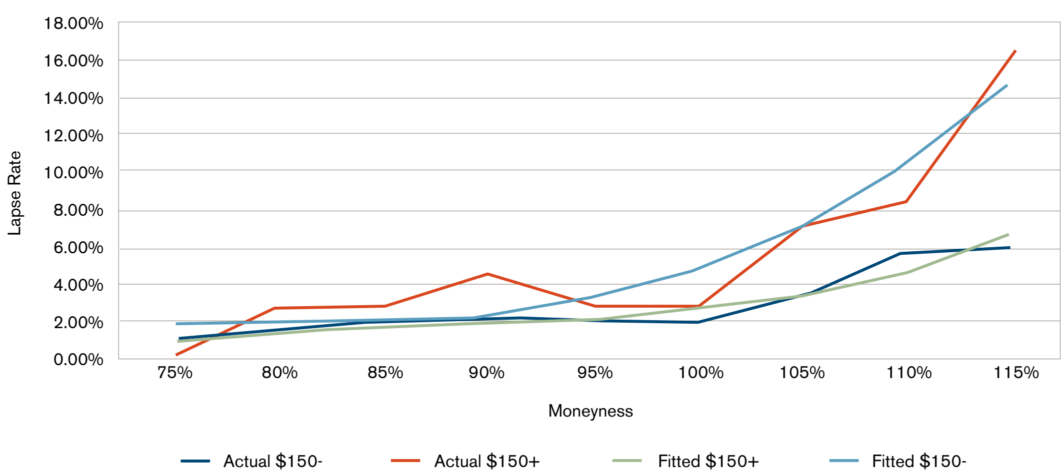
The fitted lapse rates are shown in the table in Figure 28.

FIGURE 28: FITTED LAPSE RATES BY MONEYNESS AND POLICY SIZE

LAPSE RATES BY MONEYNESS AND POLICY SIZE				
	ACTUAL LAPSE RATE		FORMULA LAPSE RATE	
MONEYNESS	$150,000-	$150,000+	$150,000-	$150,000+
75%	1.00%	0.23%	1.09%	1.92%
80%	1.45%	2.79%	1.55%	1.89%
85%	2.05%	2.86%	1.79%	1.99%
90%	2.19%	4.53%	1.96%	2.37%
95%	1.94%	2.79%	2.18%	3.22%
100%	1.93%	2.88%	2.61%	4.70%
105%	3.33%	7.16%	3.38%	6.99%
110%	5.71%	8.40%	4.62%	10.24%
115%	5.90%	16.30%	6.48%	14.63%

The fitting results are graphically illustrated in the chart in Figure 29. It can be seen that the fitted formulas represents the trend of dynamic lapse behavior quite well.

FIGURE 29: FITTED LAPSE RATES BY MONEYNESS AND POLICY SIZE



Other factors such as duration can be similarly analyzed.

CONCLUSIONS

While data-mining technology is a powerful tool in analysis, it is not enough alone to reach useful conclusions.

The principles of data mining are illustrated here, and more detailed analysis can reveal additional insight into the drivers of lapse behavior. While data-mining technology is a powerful tool in analysis, it is not enough alone to reach useful conclusions. A user's experience and understanding together with data-mining tools provide the most value.

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