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Tracking and Monitoring Claims Experience: A Practical Application of Risk Management

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BACKGROUND

This paper describes how to develop a risk management tool to track, monitor and adjust a wide variety of actuarial assumptions like mortality, lapse or morbidity embedded in the pricing and reserving for any insurance product. This is one of the most important controllable and actionable risk management tasks that a company should undertake and it will help companies reduce financial risks. This paper has been motivated by an article, "Building a Nervous System for Insurance Products" that Mark Griffin, Executive VP and CRO, Phoenix, shared with the Goldenson Center. Our paper builds on Mark's article and develops the statistical basis for identifying significant deviations in experience and determining whether it is a one-time occurrence or a trend.

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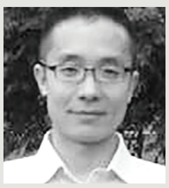

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A TWO-STEP STATISTICAL PROCESS

The risk management technique we have developed looks at two steps in the claims tracking process:

- The first step uses confidence bands to identify blocks of business whose actual experience deviates significantly from expected (pricing, reserving or any benchmark measure) in the current measurement period. This can be viewed as an early warning signal for companies.
- The second step uses historical experience and the student's t-test to check if this deviation represents a random fluctuation for the current time period or a fundamental change in actual experience.

  Note that the second step is performed only if the first step identifies a block of business which shows a significant deviation from experience in the current period. Any block of business which falls within the confidence band in the first step is not analyzed further. Also, for the second step, the current experience is excluded in the historical analysis.

POTENTIAL ERRORS IN TESTING PROCESS

Based on this methodology, there are two error probabilities which are calculated:

1. The Type 1 error denoted by α for the first test is the probability of concluding that actual experience for a given block is significant in the current measurement period when it is not.
2. The conditional Type 2 error denoted by β is the probability that given the block of business is significant in the current measurement period, the second test concludes that the underlying experience has not changed when it has.

   Note: We term this a conditional Type 2 error since we are ignoring the component of the Type 2 error where the first test is not significant but the underlying experience has changed. Our claims tracking and monitoring process only focuses on alerting management on blocks of business showing significant deviations in experience in the current measurement period and whether this significant deviation represents an underlying trend or not.

We will follow the standard approach in statistical hypothesis testing by fixing the confidence bands separately in step one and step two and calculating the various α and β probabilities for different levels of deviation in experience. A company will have to establish the appropriate confidence band parameters

"Our testing process generates two possible errors that can be measured and calibrated to fit within a company's risk threshold."

for both steps in order that the resultant Type 1 and conditional Type 2 errors are acceptable within a company's risk threshold.

METHODOLOGY SIMULATION

For a given set of confidence bands, we can simulate different values of α and β for different levels of change in underlying experience. Using mortality experience as an illustration, and denoting $q^* = actual\ mortality\ experience = 1 - (1 - q)^{(1+c)}$ and $q = expected\ mortality\ experience$, then c = 0 represents no change in the underlying mortality and c > 0 represents an adverse mortality trend. The mortality ratio A/B is the risk metric of interest where A = actual aggregate mortality experience for the current month and B = expected aggregate mortality experience for the current month.

CONSTRUCTION OF CONFIDENCE BANDS

For a two-sided confidence band in step one, it will be constructed as $[1 - factor \times SD(A/B), 1 + factor \times SD(A/B)]$ where the factor is based on the standard normal distribution for the given confidence band. Since mortality rates are available on each policy and policies are assumed to be independent, expected values and standard deviations are calculated for each policy and aggregated in calculating SD (*A/B*).

For step two, the corresponding two-sided confidence band is given by $\left[1 - factor \times SD\left(A/B\right), 1 + factor \times SD\left(A/B\right)\right]$ where $\overline{A/B}$ is the average of the historical aggregate mortality ratios and the factor is based on the t-distribution for the given confidence band where the degrees of freedom is determined by the number of historical periods being analyzed.

The Type 1 and conditional Type 2 errors have been modelled using 1,000 simulations of monthly deaths over a 24 month time period for 10,000 term insurance policies varying by issue age, duration, face amount, gender and underwriting class.

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Table 1

Step 2 CI / Step 1 CI	60%								
	c=0	c=0.01	c=0.03	c=0.05	c=0.07	c=0.09	c=0.1	c=0.15	c=0.2
80%	6.0%	7.4%	5.6%	4.9%	3.1%	1.6%	0.9%	0.2%	0.0%
85%	4.5%	5.9%	4.2%	3.7%	2.6%	1.4%	0.8%	0.2%	0.0%
90%	2.2%	4.2%	3.2%	2.6%	1.6%	0.8%	0.4%	0.2%	0.0%

Table 2

Step 2 CI / Step 1 CI	70%								
	c=0	c=0.01	c=0.03	c=0.05	c=0.07	c=0.09	c=0.1	c=0.15	c=0.2
80%	4.2%	9.7%	7.5%	6.5%	4.3%	2.4%	2.0%	0.3%	0.0%
85%	3.3%	7.8%	5.8%	5.1%	3.5%	1.9%	1.7%	0.2%	0.0%
90%	1.8%	5.3%	4.2%	3.5%	2.2%	1.2%	0.9%	0.2%	0.0%

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Table 3

Step 2 CI / Step 1 CI	80%								
	c=0	c=0.01	c=0.03	c=0.05	c=0.07	c=0.09	c=0.1	c=0.15	c=0.2
80%	2.9%	11.6%	10.4%	8.3%	7.1%	4.6%	3.4%	0.5%	0.1%
85%	2.2%	9.0%	7.9%	6.5%	5.7%	3.6%	2.8%	0.3%	0.1%
90%	1.1%	5.7%	5.5%	4.3%	3.6%	2.5%	1.7%	0.3%	0.1%

RESULTS OF SIMULATION

Tables 1, 2 and 3 show the different values of the Type 1 and conditional Type 2 errors, α and β, for different confidence bands. In our example, we have modeled a one-sided confidence band to only detect adverse mortality experience.

Note:

1. Step 1 uses the standard normal distribution to construct the confidence band denoted in the tables as Step 1 CI.

2. Step 2 uses the t-distribution with 22 degree of freedom to construct the confidence band denoted in the above tables as Step 2 CI.

3. $c = 0$ represents no change in the underlying mortality; $c > 0$ represents adverse underlying mortality.

4. The Type 1 error α represents the proportion of simulations falling outside the confidence band for step 1 and step 2 when $c = 0$.

5. The conditional Type 2 error β represents the proportion of simulations falling outside the confidence band for step 1 and falling within the confidence band for step 2 when $c > 0$.

INFERENCES FROM SIMULATION RESULTS

From the results, we can make the following inferences:

- The lower the confidence limit for the second test, the lower the conditional Type 2 error for a given confidence limit for the first test.
- The higher the confidence level for the first test, the lower the conditional Type 2 error for the second test for a given confidence limit for the second test.
- For a given set of confidence levels for test1 and test 2, the conditional Type 2 error decreases as the adverse mortality factor increases.
- For this example, an appropriate set of confidence parameters to establish could be 90 percent for step 1 and 60 percent for step 2. This generates a Type 1 error of 2.2 percent and a conditional Type 2 error of 4.2 percent for 1 percent adverse mortality, decreasing to a negligible error (zero for 1,000 simulations) for 20 percent adverse mortality.
- Our focus is on the conditional Type 2 error since our tracking and monitoring process only examines the current month's adverse experience. However, a company will have to ensure that the confidence level in step 1 is not too wide since that would reduce the need of going through step 2. This could mask the detection of any historical adverse experience that is not being captured in the current month.

CALIBRATION PROCESS

Prior to establishing a formal claims monitoring and tracking system, a company will have to establish the appropriate confidence band parameters so that the resultant Type 1 and conditional Type 2 errors are acceptable within a company's risk threshold. The Type 1 and conditional Type 2 errors are also impacted by the frequency of the claims tracking (monthly, quarterly, annually etc.) and the number of degrees of freedom in the t-test for step 2. In general, the longer the frequency of the claims tracking and the smaller the degrees of freedom, the greater the Type 1 and conditional Type 2 errors. This should be an important consideration in designing a claims tracking and monitoring process for a company.

"Claims tracking and monitoring is fundamental risk management and the benefits to a company are immediate and measurable."

TRACKING & MONITORING OUTPUT

Once the confidence band parameters have been determined as well as the tracking frequency and the number of historical periods to be tested in step 2, the claims tracking process we have developed will allow a company to identify blocks of business which show the following characteristics:

1. A significant deviation in experience in the current month and a change in underlying experience.
2. A significant deviation in experience in the current month with no change in underlying experience.
3. No significant deviation in experience in the current month.

CONCLUSION – A PRACTICAL APPLICATION OF COMPANY RISK MANAGEMENT

A disciplined and rigorous claims tracking and monitoring process can benefit a company in several ways:

1. It is an active risk management process since it identifies on a regular basis, blocks of business exhibiting adverse (or favorable) claims experience and whether it is a one-time occurrence or a change in the underlying trend, thus making it easy for a company to take any mitigating action steps.
2. It will better align the pricing, reserving and planning process of a company with the actual emergence of claims experience.
3. The process can help justify current drivers of claims experience and identify some new drivers of claims experience, thus providing a systematic way for a company to refine its claims predictive models.
4. A claims tracking and monitoring system of several actuarial decrements (mortality, morbidity, lapses) for a company could help identify correlations between risks. For example, blocks of business showing adverse lapse experience could also be the same blocks of business demonstrating adverse mortality experience.
5. It is a proactive way of dealing with regulators and analysts to explain earnings volatility arising from claims fluctuations.
6. The consolidation of a claims tracking and monitoring process of several peer companies will help develop industry best practices on how to manage claims experience and benchmark a company's own claims experience against its peers.

IDEAL FOR UNIVERSITIES WITH STRONG ACTUARIAL PROGRAMS

While many companies may lack the resources or time to develop a claims tracking and monitoring process and actively manage it, the use of actuarial resources at an accredited university which maintains strong relationships with insurance companies could be a cost-effective way to accomplish this. The Goldenson Center for Actuarial Research at the University of Connecticut has a strong actuarial program and a track record of working on actuarial research projects with the insurance industry. The Goldenson Center could undertake this initiative for its Advisory Board company representatives, which is comprised of the major insurance companies in the region. The repetitive and data-intensive nature of this project and its strong emphasis on fundamental actuarial and statistical principles makes this an ideal project to be undertaken by the Goldenson Center. Besides providing students with real-life industry experience, this will be a highly cost-effective way for companies to benefit from the academic rigor and exploratory analysis that students can provide in identifying drivers of claim experience in a disciplined and consistent manner.

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