EXPERIENCE ANALYSIS AND ITS FEEDBACK INTO THE ACTUARIAL CONTROL CYCLE

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Contents

1 Introduction

Experience investigations are a quite topical issue in India with the constitution of Mortality and Morbidity Investigation Committee in India. This paper outlines the experience study process. Further, this paper also covers the importance of the experience studies in the actuarial control cycle, data collection process, data clean-up process, the generalized exposure methods, comparing actual with expected and finally interpretation of the results and its usage for business decisions.

Currently all insurance companies in India use the LIC 1994-96 as the starting point for setting mortality assumptions for pricing and valuation. LIC 1994-96 table actually shows the mortality experienced almost 10 year back. Since then there has been radical changes in medical technology and the life style of the average Indian. On the one hand, medical science innovations may have improved quality of treatment available and hence may have well improved the mortality experience. However, on the other hand, changes in life style of average Indian could have adverse impact on the mortality and morbidity and offset treatment improvements. For example, the current young upper & middle class Indian population has increased access to powerful motor vehicles and the numbers of accident events have increased significantly. However, in the LIC1994-96 table, the usual accident hump is not evident unlike mortality experience of other markets. Thus the direction of mortality changes is not for conjecture but has to be supported by solid scientific experience investigation studies.

Experience studies is a wide topic which includes mortality investigations, morbidity investigations, lapse investigations, expense investigations etc. The focus of this paper will be to cover the mortality and morbidity investigation with some limited discussion about lapse and expense investigations. The studies usually benchmark the actual experience against a standard table, like LIC 94-96, or actual pricing assumptions.

2 Why Do Experience Studies?

The usual purpose of an experience study is to measure actual results against expected and check sufficiency of premium rates. Studies can also act as early warning systems to highlight segments that could be mis-priced and thus help refine pricing.

The data requirements could also be impacted by the purpose of the study. For example, if the study purpose is to develop mortality expectations for a new product, then the experience block considered should be consistent with current rating, pricing and underwriting guidelines. However, limiting the study data to this recent subset often leads to results that are not credible because there may only be a small number of claims. Finding a balance between including only data that is representative of contemporaneous experience vs. including data with a variety of expectations, and then making adjustments for future expectations, is both art and science.

3 The Actuarial Control Cycle and Experience Studies

Experience studies is the key element of "Monitoring the Experience" phase of the Actuarial Control Cycle. This stage deals with monitoring the experience and its feed back into the first stage i.e. "Problem Specification" stage and 2nd stage i.e. "Solution Development" stage of the actuarial control cycle.

A major part of the experience analysis is to identify the causes of any departure from the expected o utcome. This stage also help company to take appropriate steps to fix sources of problems and helps to review strategic decisions on a regular basis. It is vital for an insurance company to monitor experience to maintain/ increase market share and stay profitable. Experience investigations will allow companies to revise assumptions and models so that the company takes best informed decisions.

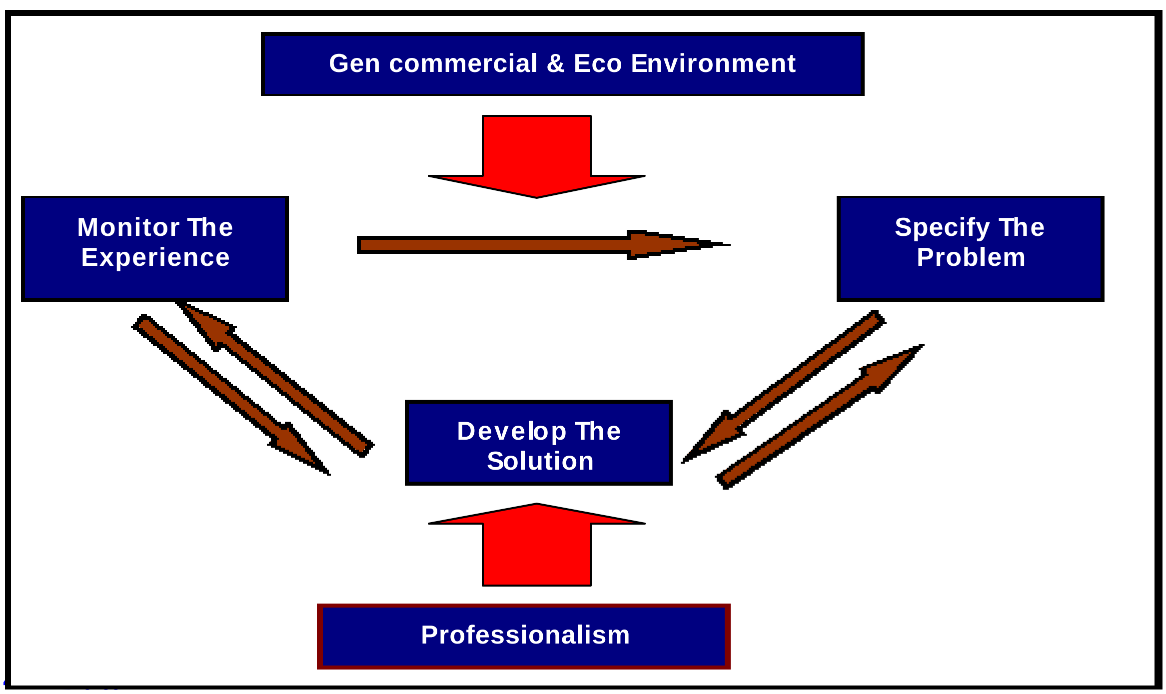
Experience studies results are also critical input for companies taking corrective actions like re-pricing of products, re-designing of product, changing investment strategy, changing sales strategies, etc.

The management of a life insurance company is just not a reactive process (in response to adverse experience) but also a pro-active one. The "Monitoring the Experience" phase helps identify things like:

- which products are profitable
- which sales channel are profitable
- which markets are more profitable
- efficient section of the business
- successful investment strategies

The picture below shows the flow of the actuarial control cycle.

Figure 1: The Actuarial Control Cycle:



Any mortality study is only as good as the data backing it. The adage "garbage in, garbage out" applies for experience studies as it does for all data analyses. Data source, collection process, present an important step toward creating a credible study.

Having a good data source is critical. For example, if the data is collected for administrative purposes, and extracting the required data is difficult, then many problems may be introduced into the study. Past reviews of such files have shown incorrect fields, transactions that don't match in-force files and even gender changes from year to year! Another common pitfall is using in-force files without their corresponding transactions. Likewise, edits and controls must be in place to uncover manual input errors and input decisions. The information used to feed financial reports or to collect premiums will likely be more reliable than "extraneous" fields for research and deve lopment.

Data verification and its corresponding cleaning can frequently occupy more than 50 percent of the total time required to perform a study – and is often the most important step in building a quality study. Some commonly performed data verificatio ns include comparing distributions in the data with expectations, looking for duplicate records, checking for consistency between in-force and transaction records, examining individual records for abnormalities, and comparing study data against financial records. However, data verification and cleaning are not the main focus of this paper.

The data needs to be consistent and stable during the period of investigation. In an ideal world we expect the data to be sufficiently homogeneous at least according to critical risk factors but in a real world this has to be balanced against the risk of creating data cells that have too little data to be credible. In practice the level of classification of data will depend upon the volume of data available, but usually it is desirable to separate different classes of contact.

As stated earlier, the main focus of this paper will be on mortality and morbidity investigation while touching upon some aspects of lapse, expense and investment return investigations. Before starting the experience analysis process, main decision that we need to make is the period of investigation. It is important since the mortality changes over time due to advances in the medical science, improvement in standard of living, change in life style and new diseases etc.

Ideally the period of investigation should NOT be more than 5 years, because we want to able to act as quick as possible on any recent changes in the mortality level, particularly with regards to product pricing. For instance, looking at an investigation which is based upon last 5 years of the data, will imply reaction time 3 year slower than if we were to use just 2 years data. But we also need to ensure that time interval is large enough so that there is sizeable amount of data.

In theory the data to be analyzed for experience studies need to be homogeneous. But in practice this is never possible. In practice the data need to subdivided according to factors that have, by experience, significant effect on mortality. This approach is possible if appropriate information is available and we have sufficient data to make such detailed analysis possible. The life insurance mortality/morbidity statistics are usually subdivided by :

- Gender
- Age
- Product type
- Smoker /non smoker status
- Medical/non medical (based upon underwriting level)

- Duration (years since policy issue date) or duration from start of claim from sickness termination
- Distribution channel
- Sum assured
- Occupation of policy holder
- Known impairment (existing medical conditions)

Apart from this, for sickness experience study benefit conditions such as deferred period , off period and waiting period need to be considered. A deferred period is the length of time that the insured must wait after becoming ill before the benefit payment may start. For example a badly broken hand might trigger the benefit payment with a 4 four week deferred period but the benefit would not trigger if deferred period was 26 weeks, since the hand should have healed by then. Hence it is worth noting that morbidity experience will differ significantly by the length of the deferred period in the product. The morbidity experience being heavier for products with shortest deferred period. An off period refers to the case like if a claimant joins the office after illness, but falls ill again within the "off Period", she or he can start to claim again without having to serve another deferred period. Waiting period is used by companies to reduce the anti-selection risk. It is period which must elapse after taking a policy before an illness or accident is allowable.

Certain subdivisions can't be carried out unless relevant information has been collected via the proposal form. Sometimes factors for which there is strong external evidence of the effect on the mortality may not be possible to use because the proposal form has been kept short for marketing or perhaps administrative reasons. Ideally for experience studies an actuary need to gather following data to build appropriate exposure:

- Product code or tariff code
- Gender
- Date of birth
- Date of commencement
- Date of movement
- Type of movement (e.g. claims, lapse, surrender, still in force etc.)
- Sum assured
- Client Id (or policy number)
- Sub standard risk indicator (yes/no)
- Smoker status (SMK/ NSMK)
- Extra loading / rating
- Term of policy
- Distribution channel
- Medical/non medical
- Rider benefit code, etc.

If we want to do the morbidity experience analysis, apart from the data above we need additional information on following:

- Waiting period (in days)
- Deferred period (in days)

The claims data collected will usually require information such as:

- Claims Id
- Policy Id

- Claim status (paid or open)
- Claim reporting date
- Date of claim
- Cause of claim (may be in code)
- Payment from (applicable in case of benefits like disability payment)
- Payment to (applicable to benefits like disability payment)
- Total benefit paid, etc.

5 Exposure Methods

Once the initial data-related steps are complete, the next challenge will be deciding how to calculate base exposures to use in the mortality study. The common method, the actuarial exposure method, can be summarized as follows:

1. If the policy remains in force to the end of the study window, it will be exposed from the beginning of the window or issue date (whichever is later) to the end of the study window.

2. If the policy terminates for any other reason than death, it will be exposed from the beginning of the study window or issue date (whichever is later) to when the policy leaves the cohort or at the end of the study window (whichever is earlier).

3. If the policy terminates due to death during the study period, it will receive a full year's worth of exposure in the year of death regardless of whether the study period ended before the year of exposure would have been realized.

Several problems arise from using this method to calculate exposures.

First, the method includes a flaw in not ending the exposure after a death if the policy is scheduled to end before a full year's worth of exposure has been realized. Although always crediting a full year's exposure ensures that the mortality rate will not exceed one, this unorthodox method results in a mortality rate estimate that is negatively biased and inconsistent.

Second, the actuarial method is based on the illogical assumption that the force of mortality is decreasing throughout the year (hyperbolic assumption), which is not true for most ages. Given that mortality tends to increase as one ages, this will cause the mortality rate estimate to be positively biased.

Another method, known as the **"exact" or "realized" exposure method**, eliminates problems with the actuarial exposure method and is summarized below.

1. If the policy remains in force to the end of the study window, it will be exposed from the beginning of the study window or issue date (whichever is later) to the end of the study window.

2. If the policy terminates for any reason other than death, it will be exposed from the beginning of the study window or issue date (whichever is later) to when the policy leaves the cohort or at the end of the study window (whichever is earlier).

3. If the policy terminates due to death during the study period, it will be exposed from the beginning of the study window or issue date (whichever is later) to the date of death. In this case, the mortality rate is not simply calculated by the deaths-to-exposure ratio, as with the actuarial method. For the exact exposure method, this ratio is known as the central death rate. Assuming an exponential approximation within the year, the central death rate can readily be changed into the mortality rate via the formula:

$$\text{Mortality rate} = 1 - \exp\text{\textasciicircum}(-\text{central death rate})$$

This result can be derived in a multi decrement environment using maximum likelihood estimators (MLEs) to solve for the central death rate first, and then calculate the mortality rate. It can also be shown that the MLEs are asymptotically unbiased estimators. That is, as your sample size increases, the calculated mortality rate will move closer to the true mortality rate. Furthermore, in the class of asymptotically unbiased estimators, MLEs are efficient, i.e., hold the lowest variance, thus eliminating many theoretical flaws with the actuarial exposure method. The exact exposure method assumes a continuous function and, as such, an exact moment of death is needed. In practice, only the day of death, not the exact time, is revealed.

However, slight modifications to the above formulas can account for this difference. Instead of calculating the exact exposure, exposure can be calculated based on the number of days the policy was in force. The ratio of deaths to exposure (in days) can then be translated into a yearly mortality rate via the following formula:

$$\text{Mortality rate} = 1 - (1 - \text{deaths/exposure(in days)})\text{\textasciicircum}365$$

This provides an answer very close to the solution given by the MLE above. The main problem with this approach is that it assumes a constant daily force of mortality throughout the year, when in most cases the force of mortality is increasing throughout the year. Alternate formulas in a multi-decrement environment hold an intuitive appeal since they assume a linear (increasing) distribution. However, the solution can be found only through iteration, and the relatively small difference in results is not worth the extra work. The exact exposure method assumes a continuous function and, as such, In practice, only the day of death, not the exact time, is revealed. When applied correctly, the actuarial and exact exposure methods provide very similar answers if the probability of an event is low, which is the case for most mortality studies.

Typically, results are expressed in terms of actual-to-expected (A/E) claims instead of mortality rates. If you use the exact method to calculate exposure, be careful when calculating the "expected" to ensure that the expected mortality rate, times the A/E ratio, is the true mortality rate. Only careful review of the calculation itself can ensure the proper "rate" has been computed.

When applied correctly, the actuarial and exact exposure methods provide very similar answers if the probability of an event is low, which is the case for most mortality studies. (Possible exceptions are older ages and highly substandard blocks of business.) Therefore, continuing to use the actuarial method, or a slight variation, will provide a reasonable approximation of the mortality. However, the further a company strays from either the exact or actuarial method, the less confidence the company can have in its numbers.

6 What Can Distort the Results?

As mentioned earlier, the art and science of estimating exposures of humans to the risk of death can provide significant challenges. Following considerations and examples demonstrate the precarious ground that actuaries walk when estimating exposures.

In-force snapshots. In a perfect world, exposure source data would include each relevant policy/coverage level change that takes place from issue through final policy level termination (including the effective and processed dates of the change). For simplicity, however, companies will often just use yearly or other periodic "snapshots" of in-force business to calculate the approximate exposure.

First-year terminations . New issues that terminate for reasons other than death before the end of the first calendar year will probably not be exposed at all. The result would be to understate first-year exposure and overstate duration 1 mortality. If year-end snapshots are used, a very rough estimate of the error would be one quarter of the first-year lapse rates. This assumes that policies are issued uniformly throughout the calendar year, and that lapses occur uniformly throughout the first policy year. In relatively high-lapse situations, however, the impact of not exposing first-year terminations could be significant.

Apart from above there are whole host of issues that can distort the results. These includes :

Late reported terminations. A study needs to allow time for terminations to be recorded due to grace periods, entry time and policy change notifications. Policies could be exposed for a full year, when in fact they terminated during the year, and their exposure should have been cut off. The result is to understate mortality. Although late-reported terminations are normally not a very significant factor in a mortality study, they could be. For example, assuming a 15 percent lapse rate and a two month average reporting lag on terminations - hopefully on the high side - would imply that exposure would be overstated by around .15 x (2/12), or 2.5 percent, and the A/E would be understated by around (1 - 1/.975), or 2.56 percent.

Less accurate accounting for the true timing of exposure. Using year-end in-force snapshots forces you to make assumptions about the timing of terminations, and, to some extent, new issues. This would normally not produce a significant impact, but you need to be conscious of situations where it could happen.

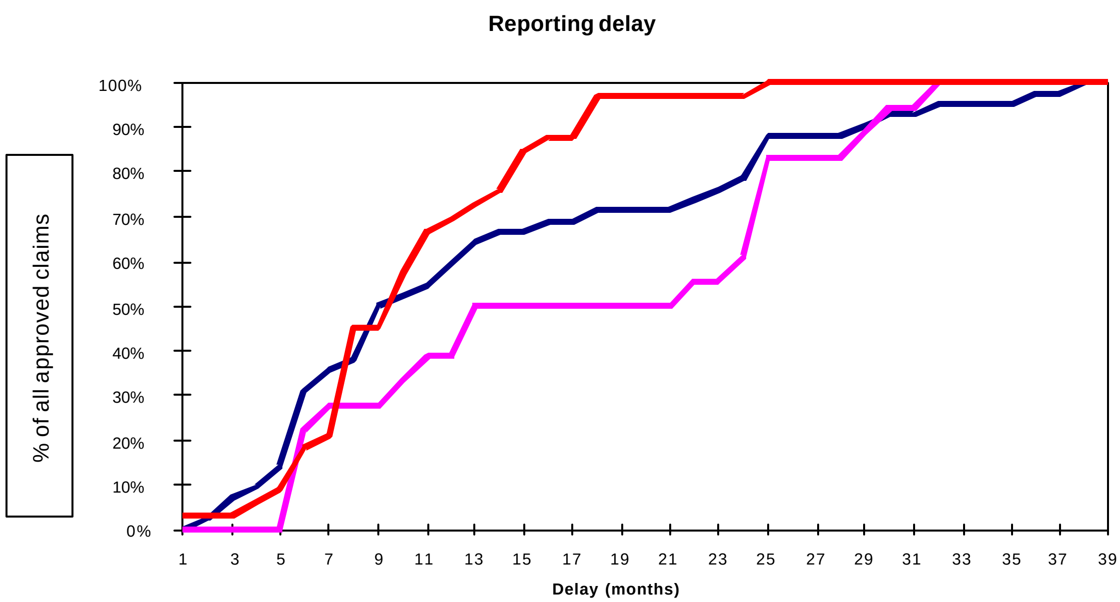
Non-homogeneous groups. As discussed earlier, the purpose of the study will determine which population to include in the study. In some situations the population needs to be relatively homogeneous, whereas for other purposes it may be more important to cover, as closely as possible, an entire block. Examples of some sub-groups that may or may not make sense to include would be substandard rated policies and policies not subject to normal underwriting, such as guaranteed issues, simplified issues and various conversions. If substandard policies are included in a study, they should normally use an expected basis that is adjusted to reflect the substandard rating or be kept in a separate cohort from the standard business

Claim amount. The amount used for a claim should generally be the same as the insurance amount being exposed at the time of death, i.e., they should generally "die as they lived." A normal exception would be to include only the amount paid on compromised claim settlements. If the amount actually paid is used across the board, it can introduce artifacts such as reduced payment due to policy loan, age adjustments and other factors. Interest and investigation expenses also should not be included since they are not relevant to the study.

Claim categories determined independently of in-force business. Mismatching errors are easy to make, are often hard to detect, and, depending on severity, can invalidate a study. Ideally, claims in the study match the exposure at the individual policy level and carry the same categorical values as when they were being exposed. Occasionally, companies find it may not be practical to do policy-level matching of claims before summarization, increasing the risk that claims will end up in different study cells than their corresponding exposure. Sometimes a simple thing such as scrutinizing claim records more than in-force records can cause a mismatch.

IBNR and pending claims. Even if the incurred claims are used, errors can be introduced by not allowing for claim reporting lag caused by the incurred but not reported (IBNR) claims or by ignoring claims still pending when the study is run. In both cases, the true claims for the study period would be understated and done so in ways that can introduce other biases. Intuitively, it makes sense that claim reporting lag time is not entirely random, so that the $5 million policy issued just last month on the spouse will probably be submitted quicker on average than the $500 paid-up policy issued in 1905 and lying in Grandpa's attic. And, as alluded to above, additional claim payment lag time i.e., the period of time a claim is "pending," would tend to be longer on contestable claims, and probably even more so on larger contestable claims. The impact of IBNR can be even greater if the claim cutoff is at the end of each calendar year, with no accounting for those claims in subsequent calendar years. The result would be a systematic understating of claims each year rather than a onetime understatement at the end of the exposure period.

Figure 2: Typical IBNR Claims Delay Patterns:



In order to avoid any possible IBNR effects and also to ensure that the share of pending claims is fairly small, the study end could be truncated earlier.

Large one-off claims or catastrophes will distort the results. The large claim can be capped at an appropriate level (and leaving the exposures unchanged). The frequency of catastrophes will have to be factored in when projecting future mortality rates.

New causes of claims such as AIDS - in most markets when the AIDS epidemic first emerged, there was no data on the effect of AIDS on insured life mortality. The actuarial community usually promulgated a general theoretical methodology for reflecting the level of AIDS mortality in the policy liabilities for individual life insurance. This general methodology used an AIDS model based on population mortality. It is important to recognize the degree to which AIDS mortality is already included in the experience data. When determining the extent to which AIDS is included in the experience, the actuary would consider the following:

- AIDS claims as a percent of total claims for own company experience relative to
- comparable industry experience or population experience;
- the degree to which AIDS deaths are reflected in experience may vary by issue date and issue age, since AIDS has emerged relatively recently;
- target markets; and
- historical underwriting standards and testing limits.
- medical changes with respect to the treatment of AIDS and the impact that these changes will likely have on mortality experience.

Select nature of the portfolio. Portfolios which have a large percentage of recently underwritten business should experience significantly lower mortality. The expected mortality assumption should be appropriately adjusted to factor this in.

The above issues illustrate some of the things to look out for in a typical mortality experience study. Other factors such as economic cycles and court rulings need to be consider for a disability study.

7 Experience Analysis Formats

It is common to state actual:expected (A/E) mortality ratios for analysing experience. As a minimum experience should be analyzed by:

- residence (urban/rural)
- policy type
- age group
- gender
- occupation class
- underwriting class
- rates/standard
- sum assured amount
- policy duration
- cause of claim

and possibly

- distribution
- date of issue

Experience by policy type

Below are the tables illustrating an example of the raw data and experience analysis across different product types (confidence interval formulae are presented in *Appendix B*):

×Policy Type

Policy Type	Start Date	End Date	Exposure	A	Crude Rate
Term	01.01.2001	01.01.2004	20'000	10	0.5
Endowment	01.01.2001	01.01.2004	500	1	2.0
CI	01.01.2002	01.01.2003	1'000	5	5.0
...	...	...	...	...	...

×Policy Type

Policy Type	Exposure	A	E	A/E : Numbers		A/E : Amounts	
				Point	95% CI	Point	95% CI
Term	20'000	10	40	25%	[15%;30%]	20%	[15%;30%]
Endowment	500	1	1	100%	[85%;130%]	80%	[70%;120%]
CI	1'000	5	3	167%	[100%;220%]	150%	[100%;200%]
...	...	...	...	...	...	...	...

There could be quite some variation in experience by policy type. Closer inspection of the results could reveal that the better experience of term policies policies as compared to endowments. The reasons for any difference, for example stricter underwriting conditions, needs to be fully investigated.

The analysis formats for age & other rating factors are presented in *Appendix A*. Below is some commentary on some issues to consider when analysing the data:

Experience by age classes

This analysis by age classes could highlight any marked differences between age groupings. If the younger ages show higher A/E ratios then this could indicate perhaps an accident hump which has not been factored into the basic pricing basis. A cause of death analysis will be needed to confirm this.

Experience by gender

Often a simplified basis is used for female rates such as rating back male rates a few years. The appropriateness of such simplifications could be gauged by an analysis of experience by gender. However, a practical problem is that female data is usually much lower in volume which reduces the credibility of the results.

Experience by occupation

Occupation, as illustrated by the often quoted UK graph below, can be a critical rating factor for mortality. To analyse the effect the appropriate occupation codes need to be captured for exposure & claims data.

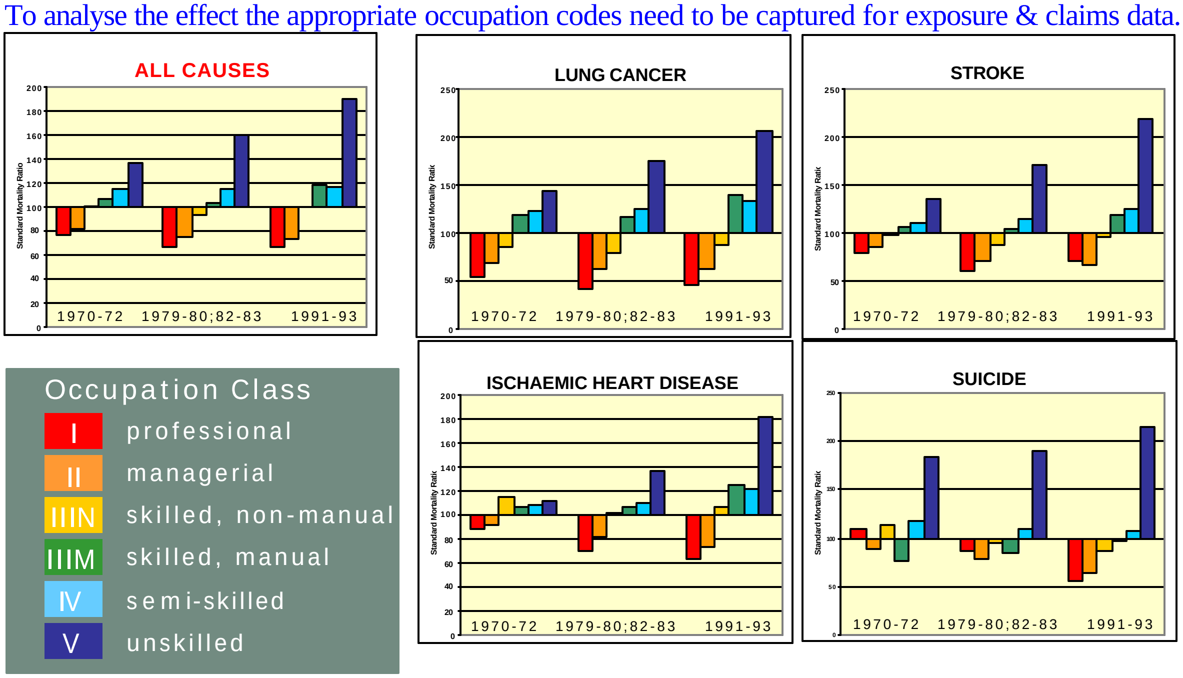


Figure 3: Mortality trends by class of occupation [England & Wales, 1970-1993]

Experience by underwriting class

This analysis by underrating classes could highlight the value of underwriting on experience. A more complete analysis is done in protective value studies which further evaluate the economic value of particular underwriting tests.

Experience by calendar year

There should be little variation of experience over a short observation period. This analysis could identify any IBNR issues with the most recent years. Also, changes in underwriting practices, etc. could be monitored.

Experience by sum assured

If experience by numbers and amounts are fairly similar, this is a first indication that experience is not likely to vary much by sum assured. This could further be confirmed when analyzing the experience by sum assured bands.

Experience by policy duration

The portfolios of the newer companies will have portfolios which are still very much in the select period for mortality experience. Hence, analyzing experience by policy duration is vital. The expected mortality could also be adjusted to take account of the temporary initial selection effect.

Multivariate risk analysis

It should be borne in mind that the analyses presented so far are univariate analyses. In order to eliminate potential confounding with other risk factors, a multivariate analysis should be carried out. There is a potential problem in the study as there is a general tendency that older persons seem to have higher sums assured. It is rather difficult to account for this effect adequately in a univariate analysis. As an example it is quite obvious that policies with high sums assured will have more underwriting. At the same time experience by the various underwriting procedures are analysed without taking into account the sum assured effect. Only a multivariate analysis would provide a good answer on the true effect of underwriting.

The Cox proportional hazard model (Cox model) is one of the most widely used multivariate survival techniques. Cox model allows multivariate exploration, handles censored data (lapses and active policies), yields tests of statistical significance and allows survival projections of specific combinations of variables. Probably the most important feature of the Cox model is the calculation of hazard ratios, which are often also referred to as risk ratios. The hazard ratio is basically analogous to a mortality/morbidity ratio (or an A/E ratio) in an experience study. A hazard ratio greater than one means reduced survival (i.e. greater risk) for an increase in the variable value. (e.g. variable values could be gender, smoker status, professional group etc, sum assured band, etc).

In doing the Cox proportional hazard analysis it will be observed that certain factors like sum assured, say, are not statistically relevant risk factors. Hazard ratios for duration can be translated into selection discounts. Hence a multivariate analysis can be a very valuable experience in fine tuning a particular pricing approach.

8 Credibility Theory

Once the experience analysis report has been completed, the results should be factored in to produce a refined pricing basis. A major component of this process is determining the level of credibility to assign to the experience. What is credibility theory? The US actuarial standard of practice note (ASoP 25) defines "credibility" as a measure of the predictive value in a given application that the actuary attaches to a particular body of data (predictive is used here in the statistical sense and not in the sense of predicting the future). Full Credibility is the level at which the subject experience is assigned full predictive value based on a selected confidence interval.

The most common application of credibility theory assesses how past experience can be combined with current mortality expectations to obtain an updated mortality assumption. The formula for this approach shows how new mortality expectations are estimated using a weighted average of past experience and current expectations. The adjusted net rate is calculated as follows:

$$\text{Adjusted Net Rate} = Z \times ER + (1 - Z) \times UR$$

where:

Z	:	Credibility factor
ER	:	Net unit rate from experience data
UR	:	Theoretical net unit rate before experience rating

In practice, past experience and current mortality expectations will be given. The problem lies in finding the credibility factor. If the experience is fully credible, this factor will be one. If the experience is not credible at all, the factor will be zero. In most cases, the factor lies somewhere in between.

The purpose of credibility procedures is to blend information from subject experience with information from one or more sets of related experience when the subject experience does not have full credibility in order to improve the estimate of expected values, or to determine when the subject experience should have full credibility and blending is unnecessary.

Again according to ASoP 25, the actuary should be familiar with and consider various methods of determining credibility. The models selected may be different for different applications. The actuary should select credibility procedures that do the following:

- produce results that are reasonable in the professional judgment of the actuary,
- do not tend to bias the results in any material way,
- are practical to implement, and
- give consideration to the need to balance responsiveness and stability.

Classical Credibility

This method uses an underlying probability distribution to help determine the appropriate level of claims needed for full credibility. Along with an underlying distribution, *Classical Credibility* assesses credibility based on two factors: an acceptable error margin (called k) for the average number of claims and a probability level (called p) that the actual claims will be within the error margin. Stated another way, *Classical Credibility* estimates with p percent certainty that the actual number of claims will be within r percent of the expected number of claims.

In most cases, the distribution of the actual number of claims is assumed to be Poisson. A normal approximation to the Poisson is then assumed to estimate the likelihood that results fall within a given range. When using these assumptions, the number of claims required for full credibility can be calculated (derived in *Appendix C*).

Assuming the number of claims has a Poisson distribution, the following formula can be applied to determine the number of claims needed for full credibility for results by amount.

Z : $= \sqrt{\dfrac{E}{n_F}}$, with a maximum of 1.

E : Expected number of claims

n_F : is the number of claims required for full credibility.

$$= \left\{\frac{Z_p}{k}\right\}^2 \times \left\{1 + \left\{\frac{\sigma}{m}\right\}^2\right\};$$

with a minimum value of 100.

where:

- Z_p is the point on the unit normal curve such that the area under the curve between $-Z_p$ and Z_p is p
- m is the mean claim size
- σ is the variance of claim size

$\left\{\frac{Z_p}{k}\right\}^2$ for different values of p & k is as follows:

p / k	0.3	0.2	0.1	0.05	0.01
0.90	30	68	**271**	**1’082**	**27’060**
0.95	43	96	**384**	**1’537**	**38’416**
0.99	74	**166**	**663**	**2’654**	**66’358**

The best values of p and k to use depend on how credibility theory is being applied. The greater a company’s tolerance for risk, the lower the number of claims needed for full credibility. Clearly, more claims are required for full credibility for higher levels of p and lower levels of k, which correspond to a more accurate estimation of the actual number of claims. While no theoretical approach exists to determine the best values to use for p and k, a common approach is to be 90 percent certain that actual results are within 5 percent of the expected mean number of claims (p=.9 and k = .05). This approach requires 1,082 claims for full credibility. Since experience with over 1,000 claims is rarely available for individual life blocks of business, a higher error margin is often used when judging credibility.

When deciding p and k levels, consideration also should be given to balance responsiveness of the mortality expectation to added experience with stability of the mortality expectation. For example, if 50 claims are available for a given subset, adding one claim should not increase the credibility factor significantly, but adding 100 claims should. The more responsive the actuary wants the mortality assumption to be the less stable results will be because empirical experience will have a greater weight.

When applying credibility theory, a good rule of thumb for the minimum number of claims that may be used to define “full credibility” is 100, based on 95 percent confidence of being within 20 percent of the mean number of claims. Results by amount would require even more claims for full credibility because of the increased variability. Because most applications to which credibility theory would be applied require results by amount, a minimum standard for full credibility may then be at least 250 claims. This number depends largely on the variability and mean of claim amounts and the accuracy with which you hope to predict future mortality expectations.

Other Forms of Credibility:

Bayesian & *Buhlmann Credibility* are alternative models to *Classical Credibility*. These details of these models are beyond the scope of the paper (see reference [3]for further details).

Bayesian Credibility is the most accurate way to determine a credibility weighted mortality assumption. However, it is difficult to apply in practice because the distribution assumptions needed are not straightforward and require a lot of judgment. Therefore, this method is usually impractical to use. It also can create biases at times because subjectivity is required in the assumptions.

Buhlmann Credibility is more theoretically sound than *Classical Credibility*. However, used in the traditional way, *Buhlmann Credibility* is less practical to apply to mortality studies because mortality needs to be estimated for a given risk class, not for exposure with an unknown risk class. It also is often difficult to get enough experience for this method to be useful. Therefore, the Buhlmann method fails the criteria of being practical to apply in most cases.

Classical Credibility is much easier to use compared to the other methods because it uses a simple formula and gives reasonable results in almost all scenarios. It also handles the problem of having limited experience because it uses underlying assumptions to judge credibility and does not rely heavily on the experience. The only criteria that Classical Credibility may not satisfy is that it may not give unbiased results because some judgment is required to apply the method.

Practical Considerations for Implementing Credibility Theory

Don't apply credibility theory in a vacuum – sound actuarial judgment remains necessary when setting mortality assumptions. Credibility theory's role is as an objective checkpoint to ensure that unwanted biases do not come into play when setting future mortality assumptions. The theory must be applied along with a thorough understanding of the business being studied. If the underlying assumptions of the theory are breached, the results may not be meaningful. Limitations to consider when using credibility theory follow:

Credibility of current expectations. In some cases, current mortality expectations are assumed to be fully credible when applying credibility theory. In practice, however, this is rarely the case. Rather, the actuary determines a weighted average of past experience and current best-estimate mortality, which is not fully credible. Even though this method is not theoretically sound, it provides a practical and reasonable approach to determine an evidence based best estimate of mortality. The amount of confidence in current expectations drives the extent to which the actuary relies on credibility theory. In other words, if the "best guess" for mortality expectations has been purely a guess, then the actuary will rely more heavily on emerging experience to set a new best estimate.

Number of claims. Credibility theory should not be applied to blocks of business with little experience. Obviously, one claim should not suggest changing expectations. A good rule of thumb would be to never use credibility theory when there are fewer than 10 deaths in a given study cell.

Context for setting assumptions. Even though credibility theory may give reasonable results, the context in which the expectation is being used drives how the mortality assumption is set. For example, increased competitive pricing pressure may cause premiums to be lower than credibility theory would suggest. Similarly, conservatism built into valuation mortality would imply rates that are too high. Even though credibility theory would suggest lower rates, this may not be suitable for valuation purposes.

Results: Number vs. amount. When applying credibility theory, factors derived using results by number of claims may not be applicable to results by amount paid in claims. Results by amount show much more variability than those by number. Factors such as average claim amount and the standard deviation of claim amounts need to be taken into consideration to derive a credibility factor by amount. The formulae presented above under the classical model does take this into account.

9 Factoring In Experience Analysis Results into Pricing

Any revision to existing mortality rates requires the actuary to exercise informed judgment, using relevant the information. The refinements to the current pricing basis is not a precise mathematical process and requires sound professional actuarial judgment and experience.

Even if experience results are extremely good, it is better to make small adjustments to the rates backed up by regular studies. This will prevent wild fluctuations in the rates. It may be prudent to impose the following limitation, for example, on experience rates:

- The revised rate is subject to a minimum of 70%, say, of the theoretical rate.
- The experience rated discount is not applied to older lives, say over 60, where data is thin. This may require some gradual reduction in the discount to get a smooth rate pattern.
- Floor on age-specific rates - to ensure prudent changes to the current basis, require the age specific rates to be greater than the upper bound of the 95% confidence interval of the experience at all ages.
- Floor on aggregate rates - require that the revised aggregate rate equal at least the credibility adjusted aggregate rate. To calculate the aggregate rate we need to make an assumption about the portfolio age distribution. This can be derived from the experience data.

References

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3. ***"Credibility Procedures Applicable to Accident & Health, Group term Life, and Property/Casualty Coverage's,*** **ASoP No. 25 (www.actuarialstandardsboard.org/asops)**

4. ***"Expected Mortality: Fully Underwritten Canadian Life Insurance Policies"***, Education Note of CIA, July 2002.

5. ***"Generalized Exposure Technique: An Introduction"*** *by Dieter S. Gaubatz, Drew A Tindall and Edward J Wright, Swiss Re Life and Health*

Appendix A: Additional Experience Analysis Formats

×Age

Age Band	Exposure	A	E	A/E : Numbers		A/E : Amounts	
				Point	95% CI	Point	95% CI
20-29	12'000	3	10	30%	[15%;40%]	28%	[15%;40%]
30-39	13'000	4	13	31%	[25%;40%]	30%	[25%;40%]
40-49	20'000	5	36	14%	[10%;20%]	15%	[10%;20%]
50-59	2'000	1	10	10%	[5%;15%]	8%	[5%;15%]
60-65	500	0	1	0%	[0%;5%]	1%	[0%;5%]

×Gender

Gender	Exposure	A	E	A/E : Numbers		A/E : Amounts	
				Point	95% CI	Point	95% CI
Female							
Male							

×SA

SA Band INR'000	Exposure	A	E	A/E : Numbers		A/E : Amounts	
				Point	95% CI	Point	95% CI
0-249							
250-499							
500-749							
750-1000							
1000+							

×Rated

rated?	Exposure	A	E	A/E : Numbers		A/E : Amounts	
				Point	95% CI	Point	95% CI
standard							
non-std.							

×Policy Duration

Policy dur	Exposure	A	E	: Numbers		A/E : Amounts	
				Point	95% CI	Point	95% CI
0-1							
1-2							
2+							

×**FCL**

Rel to FCL	Exposure	A	E	A/E : Numbers		A/E : Amounts	
				Point	95% CI	Point	95% CI
below							
above							

Appendix B: Confidence Intervals

The statistical reliability of mortality ratios depends strongly on the number of actual deaths. The significance of the resulting values is described in terms of confidence intervals (CI). The 95% confidence intervals given in the tables of this study are based on a normal distribution if the number of actual deaths is 35 or more, and on a Poisson distribution if less than 35 actual deaths occurred.

The statistical reliability of the mortality ratios depends strongly on the number of actual deaths. In sample theory, the significance of the resulting values is described in terms of “confidence intervals”. Many of the detailed results do not in themselves carry any statistically significant message, but when condensed into more general findings do serve to highlight fundamental trends.

However, interested readers can easily calculate the confidence intervals themselves: Given 35 actual deaths (A) and assuming a normal distribution, the following 95% confidence interval is obtained for A: $A \pm 1.96 \quad A$

Calculation of the confidence interval for A <35 is based on a Poisson distribution. The following table shows the 95% confidence intervals for values of A between 3 and 34:

A	**95% confidence interval**		
3	0.6	-	8.8
4	1.1.	-	10.2
5	1.6	-	11.7
6	2.2	-	13.1
7	2.8	-	14.4
8	3.5	-	15.8
9	4.1	-	17.1
10	4.8	-	18.4
11	5.5	-	19.7
12	6.2	-	21.0
13	6.9	-	22.2
14	7.7	-	23.5
15	8.4	-	24.7
16	9.1	-	26.0
18	10.7	-	28.4
20	12.2	-	30.9
22	13.8	-	33.3
24	15.4	-	35.7
26	17.0	-	38.1
28	18.6	-	40.5
30	20.2	-	42.8
32	21.9	-	45.2
34	23.5	-	47.5

Appendix C: Derivation of Classical Full Credibility Formula

The total claim out go in a particular time unit from a portfolio of "n" lives is given by
$S = X_1 + X_2 + \ldots + X_N$

where: X_i = size if the ith claim with mean "m" and standard deviation "σ", and
N = number of claims within the time unit,
a Poisson random variable with mean "nf" and variance "nf"
(where f = claim probability)

Then S is clearly has compound Poisson distribution with the following characteristics.

Mean = E(S) = E(X) E(N) = mnf……………………………………(1)

$$\text{Variance} = \text{Var}(S) = E(N)\,\text{Var}(X) + \text{Var}(N)\left\{E(X)\right\}^2$$
$$= nf\sigma^2 + nfm^2$$
$$= nf(\sigma^2 + m^2) \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

We now assume that we shall assign full credibility if the actual claim outgo is within 100k% of the expected outgo with a high probability 100p%.
In symbols:

$$\Pr\left\{(1-k)E(S) < S < (1+k)E(S)\right\} \geq p$$

$$\Rightarrow \Pr\left\{\frac{-k\,E(S)}{\sqrt{\text{Var}(S)}} < \frac{S-E(S)}{\sqrt{\text{Var}(S)}} < \frac{k\,E(S)}{\sqrt{\text{Var}(S)}}\right\} \geq p$$

$$\Rightarrow \Pr\left\{\frac{-k\,E(S)}{\sqrt{\text{Var}(S)}} < Z < \frac{k\,E(S)}{\sqrt{\text{Var}(S)}}\right\} \geq p$$

$$\Rightarrow \Pr\left\{-Z_p < Z < Z_p\right\} \geq p$$

where Z is a unit normal random variable (for large N this is a reasonable approximation); and Z_p is a point on the unit normal curve such that the area under the curve between $-Z_p$ and Z_p is equal to p.
It follows from the above; that:

$$Z_p = \frac{k\,E(S)}{\sqrt{\text{Var}(S)}} = \frac{k\,mnf}{\sqrt{nf(\sigma^2 + m^2)}} \quad \ldots \text{ substituting equations (1) and (2);}$$

$$\Rightarrow Z_p^2 = \frac{k^2 m^2 nf}{(\sigma^2 + m^2)}$$

$$\Rightarrow nf = \left\{\frac{Z_p}{k}\right\}^2 \times \left\{1 + \left\{\frac{\sigma}{m}\right\}^2\right\};$$

We can therefore assign full credibility when there is large enough experience available which we expect to give rise to "nf" claims. The extent to which the experience falls short of "nf", the credibility that can be attributed to the experience shall be reduced accordingly.

Appendix D: Mathematical proof of equivalence of exposure technique for any unit period

The experience studies using any unit period are similar if there is uniform force of decrement between the unit periods.

Let's use the relation ship between q_x and ${}^{n}q_x$
Where q_x is the annual mortality rate and ${}^{n}q_x$ refers to the mortality rate for a period of (1/n)

We know by definition,

$$q_x = {}_{(1/n)}q_x + {}_{(1/n)}p_x \times {}_{(1/n)}q_{(x+1/n)} + \ldots\ldots {}_{((n-k)/n)}p_x \times {}_{(1/n)}q_{(x+(n-k)/n)} + \ldots\ldots$$
$$\ldots\ldots.+ {}_{((n-1)/n)}p_x \times {}_{(1/n)}q_{(x+(n-1)/n)} \qquad \textbf{(1)}$$

Under the conditions that force of decrement is uniform over periods,

$${}_{(1/n)}q_x = {}_{(1/n)}q_{(x+1/n)} = \ldots\ldots\ldots\ldots. {}_{(1/n)}q_{(x+(n-k)/n)} = \ldots\ldots.= {}_{(1/n)}q_{(x+(n-1)/n)} \qquad \textbf{(2)}$$

and

$${}_{(1/n)}p_x = {}_{(1/n)}p_{(x+1/n)} = \ldots\ldots\ldots\ldots. {}_{(1/n)}p_{(x+(n-k)/n)} = \ldots\ldots.= {}_{(1/n)}p_{(x+(n-1)/n)} \qquad \textbf{(3)}$$

also

$${}_{((n-k)/n)}p_x = [\, {}_{(1/n)}p_x \,]^{(n-k)} \qquad \textbf{(4)}$$

Let's denote ${}_{(1/n)}q_x$ as ${}^{n}q_x$ and ${}_{(1/n)}p_x$ as ${}^{n}p_x$

Under the assumption of uniform distribution the equation (1) becomes,

$$q_x = {}^{n}q_x + {}^{n}q_x \times (1 - {}^{n}q_x)^1 + \ldots\ldots {}^{n}q_x \times (1 - {}^{n}q_x)^{n-k} + \ldots.+ {}^{n}q_x \times (1 - {}^{n}q_x)^{n-1} \qquad \textbf{(5)}$$

Subtracting 1 from both side,

$$1 - q_x = 1 - {}^{n}q_x - {}^{n}q_x \times (1 - {}^{n}q_x)^1 - \ldots {}^{n}q_x \times (1 - {}^{n}q_x)^{n-k} - \ldots.- {}^{n}q_x \times (1 - {}^{n}q_x)^{n-1} \qquad \textbf{(6)}$$

Expanding right side we obtain,

$$1 - q_x = 1 - n \times {}^{n}q_x + (n\times(n-1)/2) \times ({}^{n}q_x)^2 + \ldots\ldots+ (-1)^k (n(n-1) \times (n-k+1) / (2\times3\ldots\times k)) ({}^{n}q_x)^k + \ldots..$$
$$+ (-1)^n \times ({}^{n}q_x)^n \qquad \textbf{(7)}$$

$$1 - q_x = \text{for } (k=0 \text{ to } n) \, \Sigma (-{}^{n}q_x)^k \, ({}^{n}{}_{k})$$

Where $\binom{n}{k} = n! / ((n-k)!\, k!)$ **(8)**

Now the binomial theorem reduces this to

$$1-q_x = (1- {}^{n}q_x)^{n}$$ **(9)**

The common conversion formula can be used which converts an annual mortality rate q_x to its periodic equivalent ${}^{n}q_x$.

$${}^{n}q_x = 1- (1- q_x)^{1/n}$$

When n approaches Infinity, the formula $(n \times {}^{n}q_x) = m_x$ converges to a calculus function where

$$m_x = \ln (1- q_x)$$

This provides the proof for equivalence of the terms