USES OF CLOSED CLAIM DATA FOR PRICING
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I looked forward to reviewing this paper because, first, I was intrigued by the title (I couldn't understand how closed claim survey data could possibly be used for insurance pricing) and also because I thought I might learn something about closed claim surveys. It also seemed interesting to review a paper written by someone from the regulatory ranks since, as a rating organization employee, I would probably find many areas of healthy disagreement. Anyhow, here goes:

It seems that the first and most fundamental question about this paper is "how can closed claim data be used for insurance pricing without exposures?" The answer, of course, is that it can't, at least not by itself. Nobody has yet figured out a way to calculate rates without exposures (or at least premiums) and, even more important and difficult, the earned exposures must correspond to the same population and to the same time period as the losses. Perhaps it should be mentioned that from a data processing point of view, processing of exposures data is much more difficult and expensive than processing of losses, both closed and open, because there are so many more exposure transactions.

Mr. Lamb recognizes that exposures are important on page 223 when he says ... "unless the insured population is stable and your data source is universal you must have exposure indices for each ocurrence period". Actually, looking at things from the viewpoint of my employer, ISO, the population is never completely "stable" since we rarely have the the entire population and since some companies affiliate and disaffiliate with ISO each year, it is necessary to take great pains to make sure that comparable losses and exposures are present at all times. This is difficult because, for example, health care facilities may self insure one year and insure with an ISO carrier the next.

Runoff on losses must be reported long after reporting of premiums has stopped. All insurers, even doctor owned JUA's, must be made to understand their reporting obligations. For reasons such as these, even the NAIC should not blithely assume they have statistics for the entire population.

Anyhow, closed claim surveys don't capture exposures. What good are they then for ratemaking? Mr. Lamb mention several uses which I wish to discuss below:

1) TREND

Data can be used to measure severity trends. For ratemaking, two types of trend factors required are severity and frequency. Frequency trends can't be measured with closed claim survey data because no exposures are available. Severity trend, however can be measured. Some problems still exist however.

First, a long time period is required. Three or four years is probably not enough time to really measure severity trend for malpractice. The reason is that the malpractice severity for one claim can be represented mathematically as a random variable having an extremely large variance and, even if thousands of claims are collected, the variance of the mean is still rather substantial. Hence, at any given time, the average severity will fluctuate randomly about the expected value which would result from an infinite sample. Illustration: In Mr. Lamb's data, the standard deviation of the claim size distribution approximately equals \$60,000[1]. Hence, if 5,000 claims are included per year in the trend data, the average claim cost can be represented as a random variable having a standard deviation of $\$60{,}000/\sqrt{5{,}000} = \$848$.) Several years of data (7 or 8) are required to average out random fluctuations.

Second, closed claim trends can be distorted by changes in settlement patterns. Assume, for example, that small claims tend to be settled quickly, and large claims are settled more slowly and that insurers change their practices so that they fight more large claims rather than settle quickly. If this happens then initially the average closed claim severity will drop, only to rise back up again several years later. If they decide to fight more small claims, the same situation will occur in reverse.

Another distortion arises if, for example, the number of incurred claims suddenly rises appreciably (because of either increasing claim frequency or just an expanding data base). In this instance, since small claims are closed first, the closed claim data suddenly shows a temporary large influx of small claims along with a big drop in average severity.

Finally, the use of total limits data distorts trends since if insureds purchase higher policy limits over time, average claim costs will rise, all other factors held constant. To properly take this into account for ratemaking, it is necessary to know the policy limit corresponding to each claim.

On page 221, Mr. Lamb says, "using paid (i.e. closed) costs instead of incurred cost is more objective, but disregards all information about open reported claims. There is a tradeoff of advantages to be considered". I'm sure there is a tradeoff of advantages (there always is) and I also believe that use of incurred costs to determine ratemaking trends is better for slow developing lines because information on open claims is used. I'm not sure that use of paid costs is more "objective", especially in situations where reserving methods remain unchanged, but where payout patterns change. It would be nice to compare incurred trend data to closed claim trend data to check whether any of the various possible distortions are really significant. This has been done in my Attachment 1 where it is found that the two sets of data compare well in spite of the possible distortions mentioned above as well as the facts that the two sets of data were collected by two different organizations for different populations of claims.

2) LOSS DEVELOPMENT

Closed claim data can theoretically be used to measure paid loss development on either a policy year or accident year basis. Although, this is possible theoretically, in practice it would be necessary to accumulate closed claim data for over 10 years to really obtain loss development factors since malpractice claims tend to develop over long intervals. Furthermore, incurred loss development has generally been more valuable than paid loss development for medical malpractice insurance pricing since incurred loses develop much more rapidly.

[1] On page 224 , residual mean squares = 3.614×10^9 = variance of claim size distribution for an individual class and year. Standard deviation = $\sqrt{3.614 \times 10^9}$ = \$60,117

3) CLASSIFICATION DEFINITIONS

This may be the greatest application of closed claim survey data for pricing since, in a closed claim survey, much detail is requested that, for cost reasons, is not requested in statistical plans. This additional detail can be used profitably to define rate classifictions which have statistically significant differences in experience. The only problem is that the only data available is severity data, not frequency data. This is too bad since the ISO statistics tend to show that the greatest pure premium differences between the various medical malpractice rate classifications tend to be caused by frequency differences, rather than severity differences. Still, the author carries through an interesting example in which he tests whether the observed differences in average severity between four risk classifications could reasonably be due to random variation.

In the example, begining on page 240, the author reviews data consisting of losses and claims separately grouped by class within closure year. Five classes were included differentiating types of practice, i.,e. "Institutional", "Professional Corporation or Partnership", "Self-Employed", "Employed" and "Resident". Four years of data are shown. From the data, calculations were made of the overall variance of the claim distribution, and the variances of the class and years groupings (i.e. the variance "explained" by the classifications versus the "unexplained" variance).

An F-test was then performed to determine whether the variation in the data from class to class could reasonably be explained as random or whether the odds were overwhelming that real differences existed between the classes. The year to year variation (undoubtedly caused by inflation) could not possibly be attributed to random fluctuation. The class-to-class variation could be random, even though the size of the data base was large, i.e. $405,000,000.

One statement that the author makes on page 245 seemed misleading i.e. "Note that if closure years had not been included in the analysis, the residual mean squares would have been greater, the F-ratio for types of practice would have been lower and the level of significance (of the data variation on the classes) would have been greater". Although this statement is true the effect is negligibly small and in fact, no matter how the test is performed the classes can't be conclusively shown to be statistically different based upon the data provided.

CLAIM SIZE DISTRIBUTIONS

Closed claim survey data can be used to obtain claim size distributions useful for the determination of increased limits factors. As usual, there are advantages and disadvantages to using closed claim data over occurrence data for this purpose. If, for example, companies bulk reserve at all for malpractice claims, the occurrence claim size distribution would tend to be artificially distorted at the lower claim size intervals. On the other hand, since large closed claims tend to be very old, much trending is necessary to adjust closed claim distributions to a present cost level. Since any trend procedure carries with it many judgemental assumptions, the claim size distribution, based upon closed claims only, becomes largely a function of whatever trend assumptions were used.

The author discusses in depth the use of the long-normal curve as a best-fit approximation to actual claim size distributions. He finally concludes that the log-normal curve does not provide a particularly good fit by using a number of formulas for skewness and kurtosis (whatever that is) and also by calculating a "Gini Index of Concentration". One thing that surprised me about all this was that I think he could have proved the same thing (perhaps better) by doing a chi-square test on the data.

The chi-square test is much more widely known and is, in fact, included in the material which must be mastered to pass the Part 2 CAS exam. I have attached to this review (Attachment 2) a chi-square test of the closed claim data which seems to show that a log-normal curve does not fit malpractice claim data well. If the methods discussed by the author were actually superior, I would have liked to see a little more explanation of this.

The author also briefly discusses some of the mathematics underlying multiple regression techniques. This is a subject that we have some experience with at ISO since we use the multiple regression approach to develop insurance trend models, making use of forecasts of data indices external to insurance. The work that ISO is doing is difficult, not so much because of the mathematics involved, but because judgement and experience is required to properly select the external indices (if they exist at all) and to judiciously interpret the results. The author doesn't really discuss any specific applications of multiple regression techniques which relate to insurance pricing.

Two other mathematical techniques that the author briefly mentions are Discriminant Analysis and Factor Analysis. I didn't know anything about either of these before I read the paper and don't know much now, other than that both techniques are "highly sophisticated" and "extremely complex." Apparently these methods can be used to, for example, evaluate the likelihood of a claim being paid given many details about the claim and about other claims paid previously. One statement I found puzzling was that "the exclusion of incidents which have not produced claims may not seriously reduce the predictive accuracy in many instances."

Overall, I found the paper interesting and informative, to some extent because the author often expresses a point of view different from that which I normally hear at a rating organization. I certainly share the author's conclusion that we should strive to find better ways to evaluate the confusing array of data (all data including closed claim data) that we are paid to work with.

Attachment 1

COMPARISON OF AVERAGE
CLOSED CLAIM SEVERITY DATA WITH
POLICY YEAR AVERAGE INCURRED SEVERITY DATA

PHYSICIANS, SURGEONS AND DENTISTS

(1) Policy Year Ended	(2) Average Incurred Severity (000's)	(3) Closure Year	(4) Average Paid Severity (000's)
12/31/70	$16.8		
12/31/71	20.8		
12/31/72	19.7	1975	$20.8
12/31/73	22.9	1976	21.3
12/31/74	24.2	1977	24.2
12/31/75	34.0	1978	32.7

Explanation:

Data in column (2) is ISO total limits increased severity data for all physicians, surgeons and dentists classifications reported to ISO. Losses include all allocated loss adjustment expenses, are evaluated as of March 3, 1978 and are developed to 135 months of maturity.

Data in column (4) is taken from page 242 of Mr. Lamb's paper. Losses are divided by claims for each of the four years shown for all of the classes combined.

Attachment 2

DETERMINATION OF WHETHER LOG-NORMAL CURVE
PROVIDES REASONABLE FIT TO CLAIM SIZE DISTRIBUTION DATA
USING CHI - SQUARE TEST

(1) Size of Claim	(2) Ln of Size	(3) Number of Claims	(4) Expected Number of Claims	(5) $\frac{((3)-(4))^2}{(4)}$
\$ 1 to \$ 1,999	0 to 7.60	80	90.6	1.240
2,000 to 4,999	7.60 to 8.52	101	81.9	4.454
5,000 to 9,999	8.52 to 9.21	64	70.0	.514
10,000 to 19,999	9.21 to 9.90	55	64.6	1.427
20,000 to 49,999	9.90 to 10.82	59	62.7	.218
50,000 to 99,999	10.82 to 11.51	32	27.1	.886
100,000 to 199,999	11.51 to 12.21	19	14.1	1.703
200,000 and over	12.21 and over	10	9.0	.111
				10.553

Explanation:

Columns (1) and (3) are taken from the closed claim survey data on page 237 of the paper. The numbers in column (4) are determined by assuming that the number of claims per unit log-interval is normally distributed with mean 8.89 and standard deviation 1.64 (taken from paper). The Chi-square test simply assumes that:

(a) Within a given interval the actual number of claims in a sample can be represented by a random variable with a Poisson distribution where the expected number of claims equals the variance. (This should be a good assumption for malpractice claims where multiple related claims are uncommon). When the expected number of claims exceeds 10, the distribution essentially becomes Normal.

(b) The numbers listed in column (5) are each Chi-square distributed, each with order 1. The sum of the numbers should be Chi-square distributed with order 8-3 = 5. 3 degrees of freedom should be subtracted because the mean and standard deviation are taken from the data sample and the number of claims in the 8th interval is automatically determined by subtracting the first 7 from the total.

Conclusion:

The total of column (5) equals 10.553. For a Chi-square distribution with 5 degrees of freedom, the statistic should be less than 9.236 90% of the time. Hence it is concluded that the log-normal curve does not fit the data well.