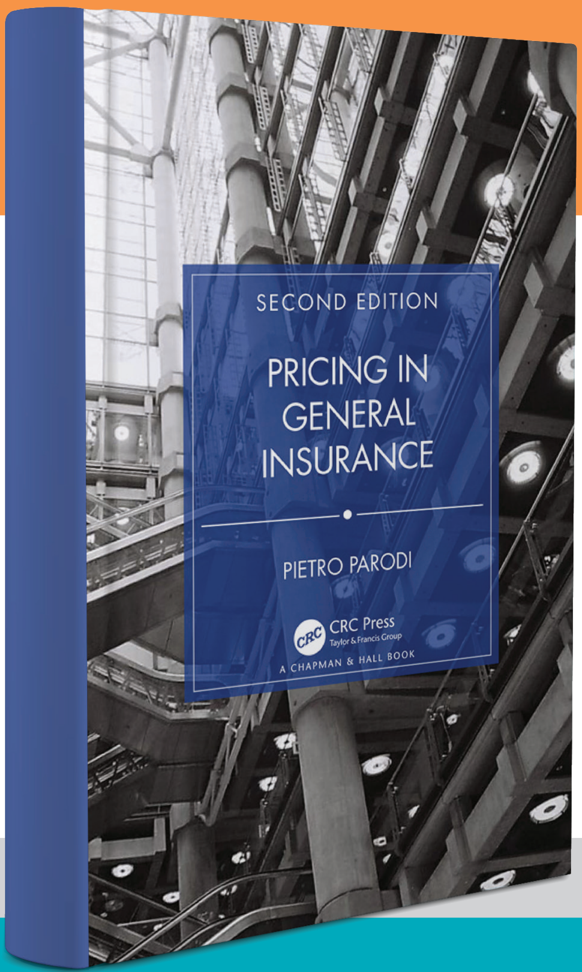

فراخوان
ترجمه کتاب

پژوهشکده بیمه

پژوهشکده بیمه، به منظور کمک به گسترش دانش بیمه‌ای، ترجمه کتاب

PRICING IN GENERAL INSURANCE

را در دستور کار خود قرار داده است. لذا از کلیه اساتید، پژوهشگران، صاحبنظران و کارشناسان دعوت می‌شود که در صورت تمایل به ترجمه کتاب مذکور، کاربرگ درخواست ترجمه پیوست را به همراه سوابق علمی و اجرایی خود و ترجمه صفحات ذکر شده با ذکر عنوان کتاب، حداکثر تا تاریخ ۱۴۰۲/۱۱/۰۷ به آدرس ایمیل nashr@irc.ac.ir ارسال فرمایند.

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الف- اطلاعات عمومی

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آخرین مدرک تحصیلی و رشته	
آدرس	
شماره تماس ثابت	
شماره تماس همراه	
پست الکترونیک	

ب- سابقه تألیف/ترجمه (حداقل ۳ عنوان از آثار خود را اعلام بفرمائید)

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ردیف	محل خدمت	مدت زمان خدمت

3.3 Reinsurance

Reinsurance (and especially treaty reinsurance) policies have among the most complex structures around, with such features as indexation clauses, premium reinstatements, and the hours clause that are difficult for those that are not insurance professional to grasp. But then again, reinsurance policies *are* purchased by insurance professionals!

5.7.2 Underwriting Function

Underwriters decide (within the limits of their authority and in collaboration with the other functions) which risks the company should accept and how they should be priced. Underwriters have an increasingly tighter relationship with pricing actuaries in a market such as the London Market.

Actuaries will normally provide underwriters with an estimated cost for the policy, and possibly with a technical premium, and the underwriter will then make the commercial decision within certain parameters. On the other hand, underwriters provide actuaries with the context and with assumptions, such as on what is exactly included in the policies (in terms of cover, territories, exclusions, etc.) and what losses should therefore be included in the historical loss analysis.

Also, actuaries and underwriters will work together in product development and the pricing of non-standard products, such as multi-class, multi-year products that modify risk profiles and cash flows.

5.7.6 Finance

The finance function is in charge (among other things) of raising the capital necessary to run the company and choosing the projects that make the best use of the company's resources based on risk and return. It is in charge, among other things, of financial reporting/accounting, treasury management, relationship with the regulator and relationship with the rating agencies.

8.4 Portfolio and Market Data

Portfolio (the wider pool of risks written by the insurer) and market information may help us in pricing where the client experience is scant. Both portfolio data and market data refer to non–client data, but we normally speak of *portfolio data* for data owned by the insurer (or an intermediary) and of *market data* for data in the public domain, accessible either freely or by subscription, such as exposure curves published by reinsurers or data available through the Insurance Services Office in the United States.

Here are some examples of how portfolio/market information can be used in practice.

a. If individual claims data sets for the same risk (such as motor or employers' liability) and for different clients (ideally, the whole market) are available, then a portfolio severity curve can be derived, which can be used to complement a client's information, or possibly replace it altogether, when the client's information is scant or non-existent. One common situation in which a client's information is scant almost by definition is the tail of severity distribution – the large losses region – therefore, it may make sense to use client's data for all losses below a certain threshold and then use a 'portfolio tail' above that threshold (see Chapter 17).
b. The property losses of a client can be modelled using an exposure curve (Chapter 22) and large liability losses can be modelled using an 'increased limit factor' market curve (Chapter 23).
c. In credibility theory, portfolio data is combined with the client's data to produce a more reliable estimate of the expected losses and hence a better premium (see Chapter 25).
d. The frequency per unit of exposure of the policyholder can be compared (and perhaps combined, using credibility theory) with that of the portfolio/market. This might apply to either the ground-up frequency or to the frequency for large losses, where the policyholder's experience is necessarily more limited (Chapter 14).
e. When reporting dates are not available for the client, the distribution of reporting delays for the portfolio can be used in its stead (Chapter 13).
f. The payment pattern and settlement pattern for claims can be rather unstable if analysed for a single client – bringing many clients together may help (Chapter 2 1).
g. Historical loss ratios for different lines of business may provide a guide for what loadings on the expected losses can be achieved (Chapter 19).
h. Portfolio data can be used to estimate claims inflation for a particular risk, which is difficult to do accurately unless the data set is massive (Chapter 9).

12.3 How Do You Select a Good Model? A Foray into Machine Learning

The main thing you need to know to judge whether a model is good or not is how strong its predictive power is, or, in more technical terms, how large the prediction error is. This is the distance between the true value of the statistic we wish to measure (such as mean, variance, percentiles …) and the value predicted by the model, *in the range to which the model needs to be applied* . Anything else – the model's simplicity, its beauty, its consistency with models for other situations and whether or not the model is realistic – is ancillary to this overarching criterion of predictive power. Of course, this still leaves plenty of leeway as to the exact formulation of this criterion and the exact definition of distance we should use, what the range of applicability of the model should be, and so on.

Because all models will be affected by prediction error to some extent, the problem that in practice one tries to solve is to select the best model from a set of competing models, and this is the problem we will focus on in this section. Even if the number of models is very large and possibly infinite (but countable), this problem is infinitely simpler than trying to find the best model amongst the (uncountable) set of all possible models.

Model selection is at the core of many activities in actuarial modelling for general insurance: selecting a frequency model, selecting a severity model, selecting the correct rating factors (such as age, sex, profession …) for a personal insurance policy and much more. For this reason model selection considerations will pop up regularly in chapters ahead (see Section 12.4 for a quick summary).

How does one select the appropriate model? Consider one of the examples listed above, that of selecting a severity model, that is, the appropriate statistical distribution that fits a set of historical losses (we will look at this problem in more depth in Chapter 16). One method we often use for this purpose is to select from a number of statistical distributions (perhaps those provided by a distribution fitting tool) the one which fits the data best. Normally, the fit is very good because some of the distributions at our disposal have three or four parameters, and we can choose between 20 or more distributions, which is like having an extra hidden parameter. Only the weirdest data sets will not find a good match under these circumstances. This is eerily reminiscent of John von Neumann's disparaging dictum: 'With four parameters I can fit an elephant, and with five I can make him wiggle his trunk'.

If model selection were about picking models that look nice when plotted against the historical losses, we should look no further than this approach. However, model selection is actually about finding models that have predictive power when applied to data *you haven't seen* (or used) before: for example, next year's losses or data you have set aside for validation purposes (Figure 12.5).

17.4.1 Practical Issues

The Monte Carlo simulation is arguably the most flexible method for calculating the aggregate loss distribution. However,

- Achieving a good precision in the calculation of the quantiles requires a large number of simulations, making the methodology slow.
- What is worse, the number of simulations needed to achieve the desired level of accuracy cannot be known in advance (see, e.g. Shevchenko, 2010). In practice, one needs to continue performing simulations until the convergence of the desired quantiles is observed empirically.
- Also, calculation of the quantiles requires sorting all the simulated scenarios and therefore storing all the scenarios in the computer's memory, which may be challenging when the number of simulations is very large, although special techniques are available to deal with this problem (Shevchenko, 2010).

To be more specific on the issue of computational complexity, the number of operations T required for running a Monte Carlo simulation is proportional to the number of simulations n_{sim} and for each simulation to the expected number of losses, λ: $T(n_{\text{sim}}, \lambda) \propto n_{\text{sim}} \lambda$. Techniques to make convergence quicker, such as stratified sampling, will not change these relationships but will reduce the proportionality constant. The quantiles then need to be sorted, which require a number of operations proportional to $n_{\text{sim}} \times \log(n_{\text{sim}})$ with some algorithms.

One specific advantage of the Monte Carlo simulation from the computational point is that the generation of the n_{sim} different scenarios can be fully parallelised. Theoretically, *all* simulations could be run in parallel if one had n_{sim} different processors, and sorting could be performed in time proportional to $\log(n_{\text{sim}})$. With the availability of parallel cloud computing, this is a consideration that needs to be made in the development of professional simulation algorithms.

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Exposure Rating for Property Insurance

Exposure rating is a method to price an insurance policy when the data for a specific client is not sufficient to produce a reliable severity model. It relies on the use of so-called ‘exposure curves’, which are reengineered severity curves and are usually based on losses from a large number of clients, as collected by large institutions such as Lloyd’s of London or Swiss Re. Ultimately, however, the origins of many of the exposure curves used by underwriters and actuaries in the London market remain mysterious.

Exposure rating was initially developed in the context of treaty property reinsurance; however, its use is now common in both reinsurance and direct insurance.

We will start by looking at the inadequacy of standard experience rating when applied to property risks (Section 22.1). We will then look at exposure curves in some detail: how they naturally arise in the context of pricing a layer of (re)insurance (Section 22.2), what relationship they have with severity curves (Section 22.3), what their main properties are (Section 22.4). The standard Bernegger (MBBEFD) curves are introduced in Section 22.5 . Section 22.6 explains how one can derive exposure curves from scratch when sufficient data is available.

Having laid the foundational aspects of exposure rating, Sections 22.7 and 22.8 describe at length the exposure rating process in reinsurance and direct reinsurance respectively. The issue of combining experience rating with exposure rating and that of incorporating cat risks are also addressed, along with more advanced issues such as MPL uncertainty and the presence of non-scalable losses.

Although much of the chapter assumes that the insured interest are buildings, plants, and so on, the same principles apply to any property-like line of business such as Marine/Aviation Hull or Fine Art, where there is a schedule of insured items each of which has an insured value and the maximum possible loss that it may incur.

25.7 What Role for Actuaries?

Actuaries need to know about catastrophe models because consideration of catastrophes must inform their activity in pricing, reserving, and capital modelling. Specifically, an allowance for catastrophes needs to be made in *pricing* , especially in the pricing of property risk, because the possibility of a catastrophe obviously affects the total losses expected for a policy. Catastrophes will also be one of the main causes of volatility of the results for an insurer's property portfolio and this will have an impact on the *capital requirements* , which in turn will affect the capital allocated to each policy (Chapter 19).

But do actuaries actually do catastrophe modelling? Actuaries do have a role to play in catastrophe modelling, but this role is by no means central. The development of catastrophe models is, in practice – as we have already mentioned – mostly the reserve of specialised companies that employ scientists, software developers, statisticians, engineers, and financial professionals (including actuaries). The running of catastrophe models and the interpretation of their outputs is also normally done by professionals who have a specific background and training in the relevant sciences and the relevant software. An ideally balanced catastrophe modelling team in an insurer, an insurance broker or a consultant should include:

- Analysts with a background in the physical sciences (such as geology, geophysics, geography) who start from a vantage point in understanding the hazards.
- Analysts with a background in engineering (such as structural engineering) who will be comfortable with the vulnerability component.
- Mathematicians and actuaries who will be comfortable in running and interpreting the financial component, especially when it is necessary to test unfamiliar structures or combine the outputs of a catastrophe model with other more traditional actuarial models, for example, in pricing complex structures involving many different lines of business.

Despite the different specialisations, however, professionals in a catastrophe modelling team will be familiar with all the components of a catastrophe model and will be able to run a standard exercise from start to finish.

Whether or not they are embedded in a catastrophe modelling team, it should be clear that actuaries need to acquire some familiarity with the outputs of catastrophe models especially if modelling property risk and need to be able to use these outputs to run simulations and assess the effect of catastrophes in pricing.

28.3 Machine Learning Techniques

As mentioned at the beginning, all these techniques to tackle MLFs can be understood in the framework of machine learning, and specifically can be seen as example of **unsupervised learning** .

Unsupervised learning – that is, learning without a teacher – is a form of exploratory analysis by which one finds patterns in the data and uses these patterns to simplify the representation of the data for further analysis. As explained in Hastie et al. (2001) , one the main problems that unsupervised learning focuses on is clustering, which can be described informally as the attempt to 'segment the data points into sets such that points in the same set are as similar to each other and points in different sets are as dissimilar as possible' (Parodi, 2012a).

The problem of reducing the number of levels in multilevel factor is quite clearly a problem of clustering. Car models can be grouped into clusters of models with similar characteristics. Postcodes can be grouped into clusters with similar risk level. Once the clusters are obtained, these can be used as macro-levels for, e.g., a generalised linear model.

Examples of clustering techniques are (list lifted verbatim from Parodi, 2012a):

- Partitioning techniques (K-means, K-medoids, EM), which partition data based on a given dissimilarity measure.
- Hierarchical methods, which subdivide data by a successive number of splits.
- Spectral clustering, which works by graph partitioning techniques after a transformation into a suitable space.
- Dimensionality reduction techniques (principal component analysis, self-organising maps (SOMs), generative topographic mapping, etc), which are based on the observation that often the data points lie in (possibly non-linear) low-dimensional manifolds embedded in a data space with many more dimensions.
- Other: density-based methods, grid methods, kernel clustering.