Preface

We are pleased to welcome you all to the Cherry Bud Workshop 2005 "Quantitative Risk Management: Theory and Practice" held in Yokohama on the 23-26 February 2005. We hope that you will enjoy the workshop and have a stimulating time, both personally and professionally.

This workshop follows on from the first Cherry Bud Workshop held on the 21-23 March 2004. The focus of the first workshop was on modelling large-scale complex systems that occur in the natural and social sciences, with a view to better understanding the large-scale dynamics, among other aspects, that underpin such systems. The focus of the Cherry Bud Workshop 2005 is on quantitative risk management and it forms part of Keio University's 21st Century COE programme "Integrative Mathematical Sciences: Progress in Mathematics Motivated by Natural and Social Phenomena".

Risk management is a key requirement for modern living that now extends well beyond its origins in insurance. The need for risk management arises in many other areas including finance and banking (value at risk, market, credit and operational risk), natural hazards (climate, earthquakes, floods etc) among many other applications. The enormous growth in this field has led to a need for integrative research in quantitative risk management which spans such diverse application areas and is securely based on data science and stochastic modelling.

Professor Paul Embrechts (ETH Zurich, Switzerland), a leading international expert in financial mathematics and stochastic risk modelling, is presenting a two-day course on quantitative risk management just before the workshop. The material he will present is based on his forthcoming book "Quantitative Risk Management: Concepts, Techniques and Tools" with Alexander McNeil and Ruediger Frey published by Princeton University Press.

The course and workshop are intended to provide a stimulating environment for all participants to learn more about recent research and developments in this exciting, rapidly growing, and very important research area. The workshop also aims to build stronger links between academia and industry based on this common interest. Professor Embrechts' course will lay the groundwork for the workshop that follows which, in turn, will reflect a mix of research and applications spanning theory and practice.

The Keio University's 21st Century Centre of Excellence (COE) programme "Integrative Mathematical Sciences: Progress in Mathematics Motivated by Natural and Social Phenomena" is funded by the Japan Ministry of Education, Culture, Sports, Science and Technology. Details of this large programme can be found at http://coe.math.keio.ac.jp. Its aims include the promotion of international cooperation with other educational and research organizations, not only to help activate the COE's own research projects, but also to provide challenging opportunities for PhD students and postdoctoral fellows to undertake cutting-edge research working with world-class researchers.

We are pleased to acknowledge the excellent services of a strong support team led by Ms Hiromi Nakakura (COE Programme Secretary) as well as Mr Natsuhiko Kumasaka. Most importantly, we would like to thank the speakers for their contributions which have helped make the Cherry Bud Workshop such an interesting and memorable occasion for all. The end of February is a little bit earlier to experience the beauty of Japan's spring but we do hope that the workshop will provide an excellent environment for nurturing academic cherry buds and help turn them into beautiful cherry blossoms. We look forward to meeting you and wish you a stimulating and productive workshop.

Ritei Shibata (Keio University)
Convenor of the Organising Committee and Member of the COE programme.

Paul Embrechts (ETH Zurich, Switzerland)
Member of the Organising Committee and Member of the COE Advisory Board.

Makoto Maejima (Keio University)
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Peter Thomson (Statistics Research Associates)
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23 February 2005

Contents

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Quantitative Risk Management. Concepts, Techniques and Tools

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Abstract

Quantitative Risk Management (QRM) has become a key discipline in many fields of application, ranging from the financial industry (banking and insurance) to manufacturing and energy. In this short course, I will mainly start from examples from the financial industry and develop QRM tools and techniques which are also useful in a wider context. Topics to be included are :

- On the history of QRM
- Profit and Loss distributions
- Risk Measurement versus Risk Management
- Elliptical Distributions and their use in QRM
- Beyond Normality and Beyond Linear Correlation
- Copulas as a QRM Tool
- Modelling Extremes and Extremal Dependence
- Techniques for stress testing
- Scaling of Risk Measures
- Examples

The course is based on a forthcoming book: A. M. McNeil, R. Frey and P. Embrechts "Quantitative Risk Management. Concepts, Techniques and Tools", Princeton University Press, Princeton, 2005 (to appear). Besides giving an introduction to the methodology, attention will also be given to examples and numerical/statistical implementation.

Rare event simulation with heavy tails

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Abstract

Rare event simulation with heavy tails Rare event simulation is concerned with Monte Carlo simulation of probabilities $z = P(A)$ which are so small that crude Monte Carlo simulation gets into problems, because the rare event A will not occur in a realistic number of replications.

With light tails, meaning existence of exponential moments of the relevant random variables, a number of efficient algorithms have been developed. Here 'efficient' means that the variance of the simulation estimator is of the same order of magnitude as z^2. The tool is usually importance sampling, where a general principle is to look for a change of measure so close to the conditional distribution given the rare event as possible. Such a change of measure is most often identified via large deviations techniques and involves exponential family techniques.

With heavy tails, exponential moments do no exist so a different approach is required. It is far less understood than with light tails how to proceed, and efficient algorithms have basically only been developed for the case where A is the event that a sum of independent random variables exceed a large value x. In finance, this could arise for example in credit risk or Value-at-Risk evaluation for portfolios. Some of the developed algorithms use again importance sampling, but the most efficient ones which have been developed are based on conditional Monte Carlo. We survey the area, including some ongoing research on dependence and insurance risk problems.

Correlation and dependence

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Abstract

Dependence of random variables can be measured by various types of correlation coefficients. The most frequently used measure is Pearson's correlation coefficient which is a measure of pairwise dependence. However, zero correlation is not necessarily equivalent to independence of two random variables without assuming normality, although the equivalence is retained if any monotone transform of the variables is uncorrelated.

Things are more complicated if we consider conditional dependence. Two typical measures are partial and conditional correlation coefficients. It is shown that both measures coincide if the conditional expectation is linear with respect to the condition and the conditional correlation is independent of the condition, which we call Condition C. We see that Condition C is clearly satisfied if the distribution is normal, but can be satisfied without such a distributional assumption. We found that a common form of the conditional covariance matrix when Condition C is satisfied is $a\,\mathrm{diag}(\boldsymbol{a}) - \boldsymbol{a}\boldsymbol{a}^\mathsf{T}$ where $a = \sum a_i$ and this type of covariance matrix is the key element of Condition C. We can then generally define a *multiplicative covariance matrix* $\mathrm{diag}(\boldsymbol{b}) \pm \boldsymbol{a}\boldsymbol{a}^\mathsf{T}$ by allowing positive as well as negative signs in this expression and so allow more freedom for the variance. We use the terms *positive multiplicative* and *negative multiplicative* according to the sign. The multiplicative correlation matrix takes the form of $\mathrm{diag}(\mathbf{1} \mp \boldsymbol{\delta}^2) \pm \boldsymbol{\delta}\boldsymbol{\delta}^\mathsf{T}$. A necessary and sufficient condition is easily derived for the multiplicative matrix to be a correlation matrix, given $\boldsymbol{\delta}$. The condition is extended to the case of multiplicative covariance matrices, given $\boldsymbol{a}$ and $\boldsymbol{b}$.

The class of multiplicative correlation or covariance matrices has nice properties. It is characterized by the factorization of variables into a com-

mon factor and the same number of uncorrelated individual factors. It provides us with a way of checking if an one factor model is appropriate for given data, based on the estimated correlation or covariance matrix. The special type of negative covariance matrix $a\,\mathrm{diag}(\boldsymbol{a}) - \boldsymbol{a}\boldsymbol{a}^{\mathsf{T}}$ is characterized as a conditional covariance matrix given the sum of variables in the class of negative multiplicative correlation matrices. It is also shown that the multiplicative covariance class is invariant under random scaling and its unconditional variance is also multiplicative. Furthermore, the partial correlation or covariance matrix is also multiplicative if the original correlation or covariance matrix is multiplicative.

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An approach to the extreme value distribution of non-stationary process

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Abstract

The problem is how to estimate the distribution function (d.f.) $F_Z(x) = P(Z \leq x; Z := \sup X(t), t \in [0, T < \infty))$ for a non-stationary stochastic process $X(t), t \in [0, \infty)$ which describes a time variant observation $x(t), t \in [0, \infty)$. A new approach to the estimation, which is based on the assumption that considered non-stationary stochastic process can be partitioned with infinitely many independent strictly stationary stochastic processes with the finite epoch T, is presented and discussed its appropriateness based on some numerical examples and the application results for the annual maximum wind speed in Japan. The theoretical framework of the approach is as follows.

To begin with, let denote the partitioned strictly stationary stochastic process as $X_i(t)$ and define random variables $Z_i := \sup X_i(t),\ t \in [(i-1)T, iT)$. Then, the d.f. of suprema is defined as follows by means of block extreme approach and the Glivenko-Cantelli theorem [1].

$$F_Z(x) = \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} I_{(-\infty,x]}\left(\sup_t X_i(t)\right) = \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} P\left(Z_i \leq x\right) \qquad (1)$$

Since the continuous process $X_i(t)$ is assumed as a strictly stationary stochastic process, $X_i(t)$ can be handled as an independent and identically distributed (i.i.d.) random sequences by partitioning the interval $[0, T)$ with

an appropriate finite number of disjointed subpartitions $[(j-1)h, jh), j \leq [T/h]$ [2]. Therefore, the summand in the right hand side of Eq.(1) can be rewritten as follows.

$$\begin{aligned} Z_j^* &:= \sup\left(X_i(t), t \in [(j-1)h, jh)\right), j \leq [T/h] = m_i \\ &\Longrightarrow P\left(Z_i \leq x\right) = F_{Z_i}^{m_i}(x), m_i < \infty \end{aligned} \tag{2}$$

If all $m_i \approx m$, then

$$F_Z(x) = \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} F_{Z_i}^{m}(x) \tag{3}$$

On the other hand, mean parent d.f., i.e. $\overline{F} := 1/n \sum F_i$, is explicitly or implicitly used in the field of engineering. As such,

$$F_Z(x) = \widehat{F}_Z(x) := \overline{F}_Z^{m}(x) \tag{4}$$

From the inequality (geometric mean)<(arithmetic mean), a lower bound of $F_Z(x)$ can be defined by following d.f.,

$$\widetilde{F}_Z(x) = \lim_{n\to\infty} \prod_{i=1}^{n} F_{Z_i}^{m/n}(x) \tag{5}$$

and following quantile function relationships are hold.

$$Q(\alpha) \leq \widetilde{Q}(\alpha), \widehat{Q}(\alpha) < \widetilde{Q}(\alpha) \text{ for all } \alpha \tag{6}$$

$$\begin{cases} \widehat{Q}(\alpha) < Q(\alpha) \to \widetilde{Q}(\alpha) & \text{for large } \alpha \\ Q(\alpha) < \widehat{Q}(\alpha) < \widetilde{Q}(\alpha) & \text{for small } \alpha \end{cases} \tag{7}$$

in which, $Q(\alpha) := F_Z^{\leftarrow}(\alpha), \widehat{Q}(\alpha) := \widehat{F}_Z^{\leftarrow}(\alpha), \widetilde{Q}(\alpha) := \widetilde{F}_Z^{\leftarrow}(\alpha)$.

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A large scale Basel II compliant application of operational risk

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Abstract

The earnings of a large bank can be affected significantly by the occurrence of adverse events associated with day-to-day operations, for example, internal fraud, failure of critical systems or processes, extreme losses incurred by rogue traders, loss of corporate knowledge, sudden changes in policy, interest rates, etc. A decade ago, the accepted approach to measuring operational risk was to use subjective or qualitative approaches only. Operational risk was not explicitly addressed by the Basel Committee on Banking Supervision in the Basel I Accord, but since then, quantitative modelling of operational risk has evolved rapidly. In Australia, the national regulator is now applying the same detailed scrutiny of operational risk as previously for credit risk and market risk.

Implementation of the requirements of the new Basel Capital Accord (also known as Basel II, or the New Accord) is to take effect in member countries from January 2007. Basel II defines operational risk as gthe risk of losses resulting from inadequate or failed internal processes, people and systems, or external eventsh. Basel II recognises the importance of the potential impact of losses due to operational risk and requires that banks hold adequate capital to protect against these losses.

Under the Basel II framework, banks have the option of estimating operational risk using one of three approaches with increasing sensitivity to risk: (1) the Basic Indicator Approach, (2) the Standardised Approach, or (3) Advanced Measurement Approaches (AMA). The first two approaches are provided for banks with low exposure to operational risk. They require that banks hold enough capital to cover operational risk as a fixed proportion of a specified risk measure.

This talk provides a basic introduction to operational risk and describes some of the statistical issues of implementing AMA in a sophisticated software package for a major bank with high exposure to operational risk. This sets the scene for the following talk by Pavel Shevchenko on operational risk modelling and quantification.

Financial risk control: theory and practice

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Abstract

As other side of coin of ongoing financial deregulations, banks are requested on provision for a voluntary risk management system. Thus building quantitatively transparent system becomes an essential part of bank management.

Benefits of quantitative risk management are two folds; First, potential loss from banking operations is controlled within a manageable range under a certain confidence level. Second, the profitability of the each business line is evaluated rationally relative to the risk associated with.

In this presentation, our focus is the former; the financial risk control. To study this issue practically and theoretically; we address following questions: What is the reasonable risk range that we can manage and/or permit? How are profit and loss generated within a bank? How should we control the risk, or shouldnft we? How do we enforce the rules and how do such rules work? Our attempt is to give practical answers to these questions.

To study these issues theoretically; we simplify variety of banking operations into a few typical business operations by taking flows of money into consideration, a.k.a. the fund transfer system. These flows changes from time to time, hence these business operations are considered as a gstochastic flow system.h These flows are affected by the allocated risk capital, and also by earning securing mechanism including loss-controlling systems.

Three basic business operations we consider in this presentation are lending, trading, asset-liability-management (ALM). The fundamental rule in the risk management is to keep accumulated random losses within a prespecified confidence limit, which would be covered by the allocated risk capital. In other words, our goal in risk control system building is to develop quantitative methodologies, which fulfill this rule.

The profit and loss (P/L) comes form inflow and outflow of the money. At the lending division, the inflow is due to the difference between lending rate and internal borrowing rate. And outflow is lending loss plus operating cost. We set a pricing guideline so that the expected value of the P/L flow meets a certain standard. Then we set various credit limits so that unexpected losses (UL) are controlled within the allocated risk capital.

At the trading division, the P/L is an adjusted value of the market P/L minus operating cost. The market P/L is calculated as total positions delta multiplied by the corresponding market fluctuation margin during the specified period. Depends on fund requirement being surplus or deficit, the interest rate imposed on the fund differs. The final P/L value adjustment is due to this funding rate fluctuation. The individual position delta limit and loss cut rules serve as the risk control mechanism.

At the ALM division, the P/L is the adjusted GAP value minus operating cost. The asset-liability GAP value is an estimated difference in amount between the internal funding rate and a fund-raising rate for such as deposit. The GAP value is adjusted to the interest rate fluctuation during the specified period. The risk is controlled by setting GAP limits.

We must admit then discuss that for each division and each corresponding risk controlling method, there are still several problems remain unsolved.

Weather extremes and climate risk: stochastic modeling of hurricane damage

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Abstract

An important area of potential application of quantitative risk management involves natural hazards such as extreme weather events (e.g., hurricanes). The insurance/reinsurance industry pays close attention to natural hazards whose economic and societal impacts can be catastrophic. Current questions with important implications for risk management include: (1) Are there trends in the frequency and intensity of extreme weather events (perhaps associated with global climate change as part of the enhanced greenhouse effect)? (2) Is there any predictability in the aggregate statistics of economic damage of extreme weather events on time scales (e.g., annual) relevant to risk management?

These two questions are addressed for a case study of the stochastic modeling of the economic damage associated with hurricanes in the U.S. A compound Poisson process appears to be a reasonable stochastic model for the total economic damage from hurricanes on an annual time scale, with there being fairly strong evidence that the upper tail of the economic damage from individual storms is heavy (i.e., Pareto type). The answer to the first question is made more difficult because any trend in the statistical characteristics of the natural hazard is confounded with changes in societal vulnerability (i.e., a marked increase in the population along coastlines at risk to hurricanes). The impetus for the second question is the well-known statistical relationship between the annual frequency of hurricanes and the state of the El Nino-Southern Oscillation (ENSO) phenomenon.

[1]The National Center for Atmospheric Research is sponsored by the National Science Foundation.

As a relatively novel aspect of risk management, the problem of how to quantify the economic value of ENSO-based hurricane forecasts to the insurance/reinsurance industry is posed.

Discussion on structural default risk modeling for implementation[1]

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Abstract

This presentation consists of the following two studies about structural default risk modeling.

1. A filtering model where default time is defined by the first hitting time when an unobservable process reaches zero (c.f. [1])
2. A default-warning model, viewed as a version of Merton's model, which focuses on whether a firm's retained earnings in the future become negative (joint work with H. Yamauchi)

In the first study, we present a filtering model on default risk. We define a firm's default time by the first hitting time when a 1-dimensional process regarded as the firm's value reaches zero, but we assume that the process cannot be directly observed. Under such imperfect information, we aim to calculate a conditional distribution of default time with respect to observation. Consequently we can specify a hazard rate process that plays an important role in reduced-form default risk modeling, although there are many problems for implementation.

The second study is originally motivated by practical demand for improvement of default prediction using financial statements. We turn our attention to retained earnings for default prevision and use present and past forecast data about sales and incomes to obtain the probability that

[1]This research is partially supported by Grant-in-Aid for Scientific Research (A) No. 16201033 from Japan Society for the Promotion of Sciences (JSPS).

retained earnings at future account day become negative. This is just an ongoing study, but we show some illustrative consequences that imply that retained earnings can be a proceeding indicator of firms' financial distress.

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Quantification of earthquake risk and application for insurance portfolio management

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Abstract

In this presentation, we will introduce the risk management of a property and casualty (P&C) insurance company, together with the earthquake risk quantification methods.

First, we will describe the concept of P&C insurance business from the view point of risk management and capital management. As an ordinary P&C insurance company, Tokio Marine & Nichido Fire Insurance Company (TMNF) is exposed to underwriting risks, financial risks, operational risks, and so on. As the main sources of return are underwriting risks, we will focus on them in this presentation. Among underwriting risks, top risks of TMNF are earthquake and typhoon due to the geographical concentration of sales forces. The re-insurance market functions to some extent to diversify the underwriting portfolio, but not sufficient.

Second, we will explain detailed methods of quantifying earthquake risk as an example of underwriting risk evaluation. To quantify the earthquake risk mainly consists of two components, which are "hazard component" and "damage and loss component". In the hazard component, a seismic hazard curve which shows the relationship between the intensity of ground shaking and the annual probability of exceedance will be calculated. So-called "time dependency" is taken into consideration. Time dependency is the idea that as for a periodically occurring earthquake the occurrence probability

becomes higher as the time elapses. In the damage and loss component, the physical damage and monetary loss at a given seismic intensity will be calculated by using damage functions (DFs). DFs are functions that relate the intensity of ground shaking to the monetary loss. A seismic hazard curve and a DF will be combined to acquire a seismic risk curve. As for typhoon risk, that is another top risk, TMNF also use "hazard component" and "damage and loss component" for evaluation, where the hazard component is based on the climatology. Actuarial/statistical methods are used for other underwriting risks such as straight fire or product liability. After quantifying all risks, the aggregation technique is employed to acquire the enterprise-wide risk curve to test the capital adequacy.

Finally, we will comment on the issues to be solved. Among them, data quality is the most serious issue in the quantification. There might be unknown active faults. The global warming effect, that is unforeseeable, may affect on the number of typhoons to land. As there are no public organizations to store claim data, we sometimes face difficulties in estimating parameters of distributions as there are not enough data.

Insurance risk management for catastrophic events

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Abstract

The present discussion on new solvency standards for the insurance and re-insurance market (gSolvency IIh) shows that a proper Insurance Risk Management (IRM) will become of more and more importance in the near future in Europe. For many companies, catastrophic losses from windstorm, hailstorm, flood-ing or earthquake are essential contributions to the overall loss. In this presentation, we concentrate on the mathematical grounds of geophysical and actuarial statistical tools that help to estimate the corresponding loss distributions. In particular, we discuss the influence of dependence structures between natural perils, and their importance for a proper modelling of the overall loss distribution. The results are illustrated by an elaborate example from industry.

Robustness aspects in risk management

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Abstract

Modern quantitative risk management relies often on underlying stochastic models which allow the estimation of key quantities such as value at risk, expected shortfall, and volatility. In this talk we focus on financial models and discuss how robust techniques can be used in their statistical analysis.

The theory of robust statistics deals with deviations from the assumptions on the model and is concerned with the construction of statistical procedures which are still reliable and reasonably efficient in a neighborhood of the model. Therefore it can be viewed as a statistical theory dealing with approximate parametric models; see Huber (1981), Hampel, Ronchetti, Rousseeuw, Stahel(1986), and Dell'Aquila, Ronchetti (2005) for an overview.

Financial models are often estimated and tested with classical econometric procedures that do not explicitly control for the effects of small distributional deviations from the assumptions; see Knez and Ready (1997). However, because of the intrinsic complexity of financial markets and the richness of financial phenomena, we may realistically believe that some deviations from the assumptions will almost always be present when using a financial model in empirical finance. It seems therefore natural to treat financial models as approximate descriptions of the financial reality and to work with statistical procedures that can deal with some deviations from the assumed model.

Implicitly, we argue that while estimating a financial model it is important to verify first, if the majority of the data is consistent with the assumed model. If this is not the case, a more complex model can be introduced. This seems particularly meaningful in the context of empirical financial

modelling, where parameter estimates and the model selected are often the input for the pricing and hedging of financial instruments. In practice, one would like to ensure that the choice of a model used to price and hedge a financial instrument is driven by the features of the majority of the observed data rather than by single datapoints or some particular historical period.

As an illustration we re-examine the empirical evidence concerning a well-known class of one factor models for the short rate process; cf. Chan, Karolyi, Longstaff, Sanders(1992) and some recent extensions with a new statistical methodology, the Robust Generalized Method of Moments; see Ronchetti and Trojani(2001) and Dell'Aquila, Ronchetti, Trojani(2003).

A second application to GARCH models (see Mancini, Ronchetti, Trojani, 2005) confirms the usefulness of a robust analysis in revealing hidden structures.

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Quantitative risk management: practice of Japanese non-life insurance company

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Abstract

In this presentation, we discuss the quantitative risk management practice of Sompo Japan Insurance Inc, one of top three non-life insurers in Japan. As introductory remarks, we summarize risks we are currently exposed to. And we brief requirements in managing these risks. Then we move into our main topic; introducing a new model to integrate major risks that we take, specifying the model, and make some final remarks from a practical viewpoint. The model is a result of recent joint development of the Sompo Japan and the Mizuho DL Financial Technology. We paraphrase that our presentation consists of three parts.

The first part is introductory background information. We will discuss the asset and liability structure, then the major risk factors that affect our balance sheet.@In general, since Japanese non-life-insurers have long-term liabilities with guaranteed interest payments, their liability side of balance sheets is similar to life-insurersf to some extent. As a matter of fact, gfinancial risks,h these risks related to the financial market, account for more than

half of the total risk. While risk contribution is less, the insurance industry, however, concerns more on catastrophic events such as earthquakes and typhoons. The second part is about our proprietary model. Reflecting the importance of gfinancial risksh, the model is designed to cover the financial risks, such as asset investment risks and interest rate mismatch risks. The model integrates all these risks. This model has following features: (1) The model is a Monte Carlo simulation model. (2) We developed a unique scenario generator which generates major risk factors including interest rates, foreign exchange rates, stock market indices, and default rates. (3) The model evaluates our balance sheet in each scenario. (4) The total risk is presented by a distribution of balance sheet values. The third part is results when the model is applied to a real data. We highlight some empirical analyses performed and insights, comment on the purpose of each analysis.

Models for dependent credit risks and their calibration

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Abstract

We give a brief overview of the statistical approaches to modelling dependence that underlie the most important industry credit risk models. Assumptions concerning the nature of dependence between defaults crucially affect the tail of the portfolio loss distribution and thus the determination of a credit risk VaR or expected shortfall.

We then specialize to dependence modelling based on a generalization of Polya's urn scheme. Applying the theory of exchangeable sequences and martingale convergence, we justify the use of the Dirichlet-binomial distribution for modelling the number of defaults in a credit portfolio. The obtained model can be fitted easily to Standard & Poors's data, for example. We focus our attention on the problems related to the maximum-likelihood estimation of the involved parameters using the expectation-maximization algorithm.

Operational risk modelling and quantification

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Abstract

The development of Basel II Advanced Measurement Approach (AMA) for quantification of Operational Risk is of strong importance for the banks. The AMA allows to quantify operational risk capital charge using internal measurement approaches. It is expected that institutions receiving AMA accreditation will benefit by having lower capital requirements for operational risk. There is no established measurement methodology for AMA and the Basel II allows for flexibility in the approach requiring, however, addressing some important elements such as: internal data, external data, scenario analysis, and factors reflecting business environment and internal control systems. Emerging best practices share a common view that AMA based on a Loss Distribution Approach (LDA) is the soundest method.

The LDA is based on modelling of frequency and severity of individual operational risks. Given estimated frequency and severity of individual risks, the distribution of loss over all risks and corresponding regulatory capital charge (difference between Value at Risk at the 0.999 level and expected loss) can be calculated using Monte Carlo simulation method. Development of a meaningful quantitative approach to operational risk is a challenging task and rich field for new research. In this talk we address a number of important aspects in the quantification of operational risk using LDA such as:

- Data thresholds (available data are collected above some reporting threshold levels)
- Dependence between risks (e.g. copula method)

- Scaling of the external loss data
- Modelling of the risk distribution tail and insurance

Dependence of multivariate extreme value distributions

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Abstract

Risks are related to extremes and dependence. Disasters happen from extreme values of loss, and they worsen when loss values are positively dependent. Hence dependence among extreme values are important in many situations. For applications, asymptotic dependence among larger components of multivariate random variables will be realistic. Instead, here, dependence among components of multivariate extreme value distributions (**MvEV**) is examined.

As a canonical form of **MvEV**, assume that the marginals are standard Fréchet distribution with d.f. $\exp(-1/x)$, $x > 0$, and the distribution function of **MvEV** is

$$G(\boldsymbol{x}) = \exp\left(- \int_{\mathcal{S}} \bigvee_{j=1}^{d} \frac{w_j}{x_j} \, dS(\boldsymbol{w}) \right), \tag{1}$$

with

$$\int_{\mathcal{S}} w_j \, dS(\boldsymbol{w}) = 1, \quad 1 \le j \le d, \tag{2}$$

where $\bigvee$ denotes maximum, $\mathcal{S} = \{\boldsymbol{x} \in \mathcal{E} : \ ||\boldsymbol{x}|| = 1\}$, $\mathcal{E} = [0, \infty]^d \setminus \{\mathbf{0}\}$, $||\cdot||$ is a norm on $\mathcal{R}^d$ and S is a finite measure on $\mathcal{S}$. If $||\cdot||$ is 1-norm, $\mathcal{S}$ is the unit simplex.

A pair of components of (1) is independent or positively dependent. If a **MvEV** is pairwise independent, it is totally independent. If a pair of components is conditionally independent given the other components, then the pair is independent. Hence, dependence of **MvEV** is quite different form, say, multivariate normal distributions.

General discussions on **MvEV** are difficult, since **MvEV**'s have complicated structure. In the bivariate case, because of a simpler form of (1), a dependence order is naturally defined and some results are shown. If the spectrum measure is symmetrically centered and positive only in the interior of Δ some results are obtained.

Comparative risk assessment: earthquakes and other hazards

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Abstract

Risk assessment for natural hazards uses different procedures for different hazards. The procedure for earthquake risk is the best developed, and involves combining the results of three areas of research. The first is earthquake source modelling, in which we estimate the likely magnitude and frequency of occurrence of earthquakes on major faults, and also set up a spatially continuous model to represent the background activity. The second is attenuation of strong ground motion, in which we model the likely ground motion as a function of the magnitude of the earthquake and the distance to the place where our building is located. The third is the amount of damage that is caused when a building of a particular structural type is vibrated by ground motion of known severity. Combining all these gives us the Exceedance Probability (EP) curve for the specified building. This can be done for a large portfolio of assets of varying type, distributed spatially with respect to the earthquake sources. A Monte Carlo procedure is often used.

For flood risk the methodology is different, in that we can obtain from hydrological studies the flow rates in the river that correspond to a set of mean return periods. Modelling flood height is a very complicated exercise which depends on a detailed land elevation model. Damage depends critically on flood height at individual buildings. We get estimates of total damage cost at the set of return periods for which we have hydrological data, although the critical assumption is that damage levels at different buildings are well correlated from one flood to the next.

The purpose of risk assessment is to help risk managers as they make risk management decisions. So we need a measure of the risk, and in particular

a measure that describes how the risk is reduced under proposed mitigation measures. The Average Annual Loss, which is the expected value of the annual loss distribution, is not a useful measure for risk managers. Nor is the Probable Maximum Loss, which often used by insurers, because it is not a well-defined measure of the worst loss that can occur. The Conditional Expected Value is a measure that can be evaluated for a set of probability ranges, even if the EP curve is known only at a set of points and not a continuous curve. It can be used to compare risk across different hazards, and forms a basis for allocating resources for mitigation.

Regional Riskscape is a research programme which is currently under way. It seeks to assess and compare risks posed by earthquakes, volcanoes, floods, storms and tsunamis. This involves collaboration among experts from all these different fields, and the plan is to present risk assessments in a comparative way for all the five hazards. A pilot study will do this for three small areas in New Zealand, and provide risk managers with a tool to examine the priorities for mitigation expenditure and the benefits in proposed mitigation strategies.

Risk forecasting models for New Zealand hydro catchment inflows

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Abstract

The security of New Zealand's electricity supply is largely dependent on the future annual patterns of water inflows into the major hydro catchments over seasonal to multi-year timescales. The New Zealand Electricity Commission, which oversees New Zealand's electricity industry and markets, is concerned with estimating the risk of extreme annual sequences of weekly inflows so that it can take steps to mitigate the effect of dry years.

This paper describes exploratory research undertaken for the Commission. The main aim was to evaluate the feasibility of building a predictive model for weekly catchment inflows that captures the stochastic properties of historic inflow sequences sufficiently accurately to be suitable for risk forecasting, particular of extremes, and for simulating realistic forward sample realisations. More accurate and reliable stochastic models for key water inflows are also likely to lead to other benefits including better informed national energy strategies.

Following a review of published research on statistical models for New Zealand and other inflows, an exploratory analysis of the inflow data was conducted with a view to identifying suitable candidate models. These include the linear periodic autoregressive moving average (PARMA) model

which is often used to model hydrological time series and whose basic framework has served as a foundation for alternative parametric and nonparametric models. However these models cannot easily account for the evolving seasonal patterns present in the New Zealand inflows data, and the episodic nature of these patterns which can switch abruptly between regimes at times that can be earlier or later than expected. This has led to consideration of nonlinear models such as hidden Markov models (HMM) which have been widely used to model rainfall and many other episodic phenomena of this sort.

Further details of the models considered and the outcomes of the exploratory analysis are discussed, as well as recommendations that scope further developments.