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Editorial

Editorial to the special issue on modeling and measurement of multivariate risk in insurance and finance

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1. Introduction

The need to model and measure multivariate risk arises in many contexts. This special issue of *Insurance: Mathematics and Economics* focuses on problems of multivariate risk assessment in insurance and finance. A prime illustration is provided by financial conglomerates, which have to assess the risk exposure of each of their constituents (subsidiaries, business lines, portfolios, etc.) in order to determine an adequate level of surplus capital. This assessment depends critically on diversification effects and on the level of dependence between the constituents.

Recent developments in the insurance and financial industry call for appropriate multivariate risk assessment techniques. Think, e.g., of the current and upcoming solvency capital accords or the explosive growth in multi-name financial derivative products. Various problems pertaining to this theme are addressed herein using techniques that also apply more broadly.

This Editorial serves as a brief introduction and guidance to this special issue, which contains nine articles. Each of them underwent (and survived!) a strict peer-review process. Special thanks are due to David Bellhouse, Michel Denuit, Rob Kaas, Richard Lockhart, Olivier Scaillet, and Elias Shiu for their assistance in handling the submissions.

1.1. Worst-case risk measurement

Multivariate risk assessment is often hampered by a partial or complete lack of information on the nature of the interaction between several variables. In such cases, it is helpful to identify the most adverse dependence structure, given a fixed set of marginal distributions. This approach is also useful for conducting stress tests for dependence. Stress testing is spreading quickly and has already been built into the regulatory regimes of many insurance companies and financial institutions.

Concretely, worst-case analysis consists of finding bounds on the risk associated with a specific combination of random variables with fixed margins. These bounds should be as narrow as possible, given the information available on the relation between the variables. This question has a rich history in probability, where it is often referred to as the Fréchet problem.

In the first paper, Kaas, Laeven and Nelsen study the Fréchet problem for two common risk measures, the Value-at-Risk (VaR) and the Tail Value-at-Risk (T-VaR). They derive optimal bounds on these measures for functions of two variables, assuming fixed margins and partial information on dependence, e.g., the value of a measure of association. The bounds, which are explicit, turn out to be rather wide. This shows the importance of accounting for variability in the VaR and T-VaR when information is incomplete.

It has been known since the work of Makarov (1981) that comonotonicity does not always correspond to the worst VaR scenario. However, Embrechts et al. (2005) proved that this dependence structure does lead to the VaR scenario that is most adverse *on average*. This result, which holds in the absence of information on dependence, is extended in the paper by Laeven, to the case where partial information is available on the interaction between the variables. He shows, further, that in contrast to the VaR, all concave distortion risk measures, e.g., the T-VaR, achieve their worst-case performance when all variates are increasing functions of a common factor. His work illustrates the important and practical role played by comonotonic and conditionally comonotonic scenarios in VaR-based risk management.

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1.2. Aggregation of risk measures

In the process of assessing the risk of a financial conglomerate and its various constituents, the aggregation properties of the risk measure are relevant. Subadditivity, in particular, implies that it is preferable to bear the aggregate risk, rather than each of the individual risks separately.

There has been substantial debate over the desirability of subadditivity, particularly in connection with the VaR; see, e.g., Daníelsson et al. (2005) or Dhaene et al. (2008). Nevertheless, it is widely acknowledged that at probability levels of relevance for risk management, VaR properties depend on the interplay between the dependence structure and marginal tail behavior.

In their paper, Embrechts, Nešlehová and Wüthrich study the aggregation properties of the VaR in the far tail for an Archimedean dependence model with regularly varying margins. Using results of Barbe et al. (2006), they show that switching from a finite-mean to an infinite-mean model makes the VaR superadditive rather than subadditive. This observation is clearly relevant for operational risk, where partial evidence has emerged in support of infinite-mean models; see, e.g., Moscadelli (2004). But the importance of their findings is even greater when it is realized that popular subadditive alternatives to the VaR are ill-defined in such models!

1.3. Copula modeling and inference

Copula methodology is very popular in insurance and finance. It provides much flexibility for multivariate risk modeling and is well suited for stress testing for dependence. Through rank-based methods, the dependence between random variables can be estimated and validated separately from the margins. The robustness provided by nonparametric inference is also welcome.

For data sets of small or moderate size, plotting the observed pairs of (normalized) ranks yields useful clues about the relation between variables. These points form the support of Deheuvels' empirical copula, which estimates the underlying dependence structure consistently. In many applications, however, data sets are so large that scatter plots become uninformative.

In their paper, Genest, Masiello and Tribouley suggest that a smoothed histogram of ranked pairs conveys a better sense of the underlying copula density. Kernel methods could be used to this end, but non-negligible border effects arise because copula densities often take large values along the edges of their support. As an alternative, the authors propose the use of wavelets. Their solution is attractive on many accounts: in addition to being conceptually simple and easy to implement, it enjoys several optimality properties and handles the border effects automatically. In short, the wavelet method produces an integrated collection of smoothed histograms corresponding to various resolution levels, much like multiple clicks on a Google map yield successively refined photographs of a landscape.

Though nonparametric copula estimates are useful for exploratory data analysis, parametric models are often preferable, e.g., for prediction purposes. A wide variety of dependence structures are available in the bivariate case, e.g., Archimedean, meta-elliptical, and extreme-value copulas. When several risks are involved, however, the choices are more limited. In their paper, Aas, Czado, Frigessi and Bakken address this issue by showing how the pair-copula decomposition algorithm of Bedford and Cooke (2002) can be exploited to construct rich and complex multivariate dependence patterns. This approach, which parallels classical hierarchical modeling, decomposes a multivariate distribution through a series of conditionings whose basic building blocks involve only pairs of variables. The systematic way in which this is done, called a vine, ensures that any choice of bivariate copula for the building blocks yields a bona fide multivariate distribution; compatibility issues are bypassed completely! In addition to providing a very pedagogical introduction to the subject, the authors show how nonparametric estimation of the dependence parameters could proceed from the ranks of the raw data at the lowest level of the hierarchy, and from imputed observations at higher levels. Although the validity of their inference procedure remains to be established, the potential of this modeling approach is great, and clearly illustrated in a financial setting.

In the next paper, Genest, Rémillard and Beaudoin review goodness-of-fit tests for copula models. They concentrate on rank-based procedures, which make it possible to check the validity of the dependence structure separately of the margins. A blend of new and existing tests is considered; some of them were designed for specific copula families, others can be used at large. After discussing some of the critical issues associated with goodness-of-fit testing in copula models, the authors present the results of a large-scale simulation study aimed at assessing the level and power of various blanket tests, i.e., procedures whose implementation requires neither an arbitrary categorization of the data, nor any strategic choice of smoothing method, whether it be kernel- or wavelet-based, or whatever. In addition to the specific recommendations it makes, this paper shows the importance of computationally intensive methods in situations where the null distribution of the test statistic involves unknown parameters. It also emphasizes that replacing raw data by ranks can have a non-negligible effect on the finite-sample and asymptotic distributions of a test statistic.

1.4. Multivariate modeling in insurance and finance

Applications of multivariate risk assessment in the insurance and financial industry are legion. This issue contains two contributions along these lines.

In the first paper, Young, Valdez and Kohn are concerned with multivariate risk modeling in non-life insurance. More specifically, they consider conditional claim-type modeling. Contributions in this area are uncommon, in part for lack of publicly available data, but they are highly relevant because claims of different types (e.g., property damage in automobile insurance vs personal injury) often come together. The authors advocate the use of the multivariate probit model in this setting. They argue that, when dealing with correlated outcomes, this model is superior to the multinomial logistic model because it strikes a good balance between flexibility, computational tractability and statistical realism. Their approach is illustrated with detailed claim experience data, derived from motor vehicle insurance portfolios of insurance companies in Singapore. However, it could also be used profitably in operational risk management or for other forms of insurance contracts involving multiple, different claim types.

In the second paper, Schmidt and Schmieder show how multivariate elliptical processes can be used to provide a dynamic analysis of the risk associated with credit portfolios. The paucity of time series data is a major problem in this context. In order to overcome it, the authors propose a technique that achieves identification by taking into account the cross-sectional dimension via aggregate portfolio-specific risk drivers. While being invisible at the single obligor level, volatility structures turn out to become identifiable at the aggregate risk-driver level. Their approach covers all stages, from modeling and statistical inference to simulation. It is illustrated on firm data from Moody's KMV Credit Monitor, but could be applied more broadly, e.g., to other series of multivariate asset return data.

1.5. Ruin theory with dependence

The special issue's final contribution is concerned with ruin theory. In the literature on the subject, it is often assumed, for convenience, that the claim sizes and the inter-claim arrival times are mutually independent. While these assumptions ease computation of ruin measures, they may not be realistic.

In his paper, Marceau studies a discrete-time ruin model with dependence between inter-claim arrival time and corresponding claim size. Instead of assuming a specific dependence pattern, he considers various forms of association. He then studies the properties of the aggregate claim amount process, and derives expressions for some relevant ruin measures. By using these expressions, he is able to measure the effect of dependence on risk assessment, which turns out to be substantial. His work illustrates nicely the fact that dependence stress testing procedures are crucial for risk assessment in financial conglomerates.

1.6. Concluding remarks

Modeling and measurement of multivariate risk in insurance and finance is an extremely challenging and important area of research for various reasons: (i) it poses questions that are theoretically demanding and at the true boundaries of current knowledge; (ii) it is highly interdisciplinary, involving probability theory, statistics, actuarial science, mathematical finance, financial econometrics as well as microeconomic theory; and (iii) it is of major practical importance and large amounts are at stake. May this special issue stimulate further work in this important and fascinating area of research!

2. Table of contents

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