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Modeling the yearly Value-at-Risk for operational risk in Chinese commercial banks

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Abstract

In this paper, we explore the loss data collection exercise for operational risk in Chinese commercial banks from 1999 to first half of 2006. Firstly, the above data are bootstrapped to analyze the capital allocation for a medium-scaled commercial bank in China. Secondly, for every selected cell, we calibrate two truncated distributions to fit the loss severity, one for 'normal' losses and the other for the 'extreme' losses. Moreover, a more realistic dependence structure – multivariate *t* copula function is used to measure the relation among the selected cells. In the final, the simulation results suggest that substantial savings can be achieved through measuring the dependence by means of multivariate *t* copula function than by means of perfect positive dependence.

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1. Introduction

In 1988 the Basel Committee on Banking Supervision (BCBS) issued one of the most significant international regulations impacting on the financial decision of banks: the Basel Accord. Subsequently, the BCBS recognized that the capital charge related to credit risk implicitly covered other types of risk, such as operational risk. Then they worked on a revision, called the New Accord on Capital Adequacy, or Basel II (see BCBS [5,8]).

This new framework, developed by the Committee in 2002 to ensure the stability and soundness of financial systems, was based on three 'pillars': minimum capital requirements, supervisory review and market discipline. For more details, refer to BCBS [5–7] and Nash [38]. The crucial novelty of the new agreement was the identification of operational risk (OR) as a new category, and proposed a common industry definition as follows:

> "Operational risk is the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events"(Risk Management Group [42]).

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Recent years have seen a rapid and widespread development of operational risk models. This is motivated by two aspects: the regulatory compliance from authorities, the measurement and forecast from banks. It is remarkable that, many Australia banks, building societies and credit unions – collectively known as authorized deposit-taking institutions (ADIs) have been calculating and allocating operational risk for a number of years, with the Commonwealth Bank doing this since 1997. All ADIs will be required to have in place a comprehensive risk management framework for operational risk. The requirements of this framework – prudential standard released in 2006, which has championed Basel II since it was first proposed, and has pushed ADIs to comply fully with the new guidelines. And the quantitative model measuring the annual operational Value-at-Risk has gained much importance in ADIs. More comprehensive and profound assessments on Basel II implement in Australia can refer to IMF [32].

Then many methodologies for operational risk have been constantly developed to increase the soundness of business produces. While the two simplest approaches proposed by Basel II (i.e., the Basic Indicator Approach, or BIA, and the Standardized Approach, or SA) define the operational risk capital of a bank as a fraction of its gross income, the Advanced Measurement Approach (AMA) allows banks to develop their own model for assessing the regulatory capital that covers their yearly operational risk exposure within a confidence interval of 99.9%.

The two main categories above are also called 'top-down' and 'bottom-up' methods. The first approach is suitable for small banks, which prefer a cheap, easy to implement methodology (Netter and Poulsen [40]). 'Bottom-up' techniques use individual events instead to determine the source and amount of operational risk. Operational losses have been divided into levels corresponding to business lines (BLs) and events types (ETs) and risks are measured at each level and then aggregated. These techniques are particularly appropriate for large-sized banks and those operating at an active international level. Methods belonging to this class are grouped into the AMAs (BCBS [5]) and are represented by the internal measurement approach (for details, see Kuhn and Neu [34]; Alexander [1]), the scored approach (Anders [3]), the loss distribution approach (LDA) (refer to, for instance, Frachot et al. [24]; Haubenstock and Hardin [30]) and the Bayesian approach (see Cornalba and Giudici [15]; Giudici and Bilotta [28]; Valle and Giudici [44] for more details).

Among the eligible variants of AMA, the Basel II Accord specially mentions the LDA, a statistical model widely used in the insurance sector. By contrast with the BIA and SA, the LDA model lends itself to qualifying the impact of active operational risk management actions, and justifying (potentially substantial) capital reductions. The LDA model was first described in detail and used to calculate economic capital allocation by Frachot et al. in [24]. From then on, much literature has been developed to deal with operational risk via the variants of LDA. For instance, Frachot et al. [25] continued to describe step by step how a full LDA can be implemented in practice and how both quantitative and qualitative points of view can be reconciled. The Monte Carlo simulation method was utilized to determine the loss distribution and the relative risk measures like Value-at-Risk (VaR) or Expected Shortfall (ES) by Clemente and Romano [14]. Embrechts et al. [19] reviewed four methods for calculating the compound distribution function of total losses and pointed out that even extreme value theory can also reach its limit in OR modeling. And a numerical procedure to obtain bounds on the distribution of a sum of n dependent risks having fixed marginals was subsequently derived by Embrechts and Puccetti [22]. Chavez-Demoulin et al. [12] investigated so-called 'embedding' method which was of particular use for modeling dependent losses trigged by a common effect. Practical methods for measuring and managing operational risk in the financial sector was proposed by Chapelle et al. [11]. For more details on this issue, the interested readers can refer to Embrechts et al. [21,23], Degen et al. [16], Bachelier [4], Carvalho and Marinho [10], Havlický [31], Jimmy et al. [33] and Valle and Giudici [44].

As we know, there are two main problems in OR modeling, one is the inaccuracy and scarcity of data, and the other is the assumption that perfect positive dependence between all 56 risk categories in Basel II matrix is too simple and not coincide with real OR data. Our work can be seen as an attempt to overcome these shortcomings. We opt for bootstrapping the OR data to deal with the first problem, however the employments of Bayesian and simulation methods are another natural solution to this. With respect to the second question, multivariate t copula function will be calibrated to model the dependence between the selected several cells from Basel II matrix.

The rest of this paper is organized as follows. Section 2 outlines the bootstrapped loss frequency and severity data which stemmed from the loss data collection exercise for operational risk in Chinese commercial banks from 1999 to first half of 2006. Section 3 illustrates in detail the methodology we use in the selected cells, with particular focus on the description of simulation methods. In Section 4, we calculate the total Value-at-Risk for the selected cells by means of t copula (conducted with the Matlab software, Release 2008a), and compare with the total Value-at-Risk which was carried out by perfect positive dependence between different cells.